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Long Observation Window Reveals the Relationship between the Local Earth Magnetic Field and Acute Myocardial Infarction

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Abstract: A substantial body of research has demonstrated the relationships between cardiac arrhythmias and geomagnetic activity. In this work, the idea is centered on finding the relationship between the local magnetic field (LMF) and acute myocardial infarction (AMI). It is hypothesized and demonstrated via a series of statistical analyses that the relationship between the LMF and AMI is maintained over long-term observation windows. The data are collected from the two hospitals and one public institute of health in Lithuania from 2014 till 2019. The data are categorized into (1) daily average of the Schumann resonance for the local magnetic field measured by the Lithuanian magnetometer, which is used as the input variable; and (2) the total number of patients hospitalized in Lithuania per day with the diagnosis of AMI (the output variable). The data are classified both weekly as well as by gender. Following the data categorization and classification, the data were subjected to rigorous statistical analysis to determine the relationship between the input and output variables. This paper shows that only the beta and gamma (S-beta, S-gamma) frequency ranges of the Schumann resonances contribute to maintaining the long-term relationship between the LMF and AMI.

Keywords: acute myocardial infarction; local earth magnetic field; statistical analysis; Schumann resonances



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1. Introduction

Heart disorders are the leading cause of mortality worldwide and research studies on the numerous cardiovascular diseases have long been a major topic of interest. One of the most pressing study topics in cardiovascular disease is acute myocardial infarction (AMI) and the worldwide mortality it causes. AMI is a major cause of hospital admissions and deaths worldwide [1,2]. It is well-known that risk factors such as stress, smoking, obesity, comorbidities, and unhealthy lifestyle are accountable for AMI pathogenesis. However, there is growing evidence showing the existence of other, more complex factors which are also responsible for AMI, such as ambient temperature fluctuations, humidity, and atmospheric pressure [3–9].

Low ambient temperature is one of the essential factors for the onset of AMI for medium-latitude populations and is more critical than physical exertion or psychological stress. Increased mortality due to AMI in association with fluctuations in ambient temperature have been reported around the world [10–12]. An alternative study claims that a decrease in the ambient temperature by 10 degrees Celsius increases the risk of AMI by 10 percent [13]. The last observation is also confirmed in [14].

The importance of atmospheric pressure on cardiovascular events has been highlighted in [15]. A 10-bar decrease or increase in pressure below or above 1016 mbar is associated with 12 and 11 percent increased incidences, respectively. Ozheredov et al. reported in [16] that increasing atmospheric pressure positively correlates with arterial blood pressure, indicating the influence of atmospheric pressure on AMI.

Studies from China found that cold weather, in combination with air pollution, has the strongest effect on cardiovascular mortality [17]. Consistent with this, air and water pollution are considered factors severely triggering AMI in addition to strokes, cardiac arrhythmias, and pulmonary diseases [17].

It is well-known that environmental factors such as daylight (and circadian rhythms in general) have a pronounced effect on human mental and physical condition [18]. The disruption of circadian rhythms has a negative effect on morbidity and mortality due to heart diseases. AMI has a significant correlation to the circadian rhythm [19]. The relationship between the circadian periodicity and AMI has been repeatedly proven in several studies [20,21].

It was found that GSs may significantly increase platelet aggregation, blood coagulation, and its viscosity in addition to decreased blood flow in small and medium vessels [21]. It is also reported that solar activity and its wind-forming geomagnetic storms (GSs) may have effects on human health [22,23]. In contrast, the increased LMF activity in higher frequency ranges yields a positive correlation with ischemic cardiac events. The impact of the local earth magnetic field (LMF) on cardiovascular events has also been reported in the scientific literature during recent years. For instance, it is reported that increased LMF activity at various frequencies can have effects on individuals, for example, increased LMF activity in low-frequency ranges is related with an increased occurrence of acute cardiac arrhythmias [23].

It is shown in [24] that an increased LMF does have a negative influence on the sensitivity of baroreceptors, which are involved in the self-organization of heart rhythm variability (HRV). It is shown in [25] that the diastolic blood pressure reduces at least 2 mmHg, and the capillary blood flow increases at least 17 percent, when patients are placed into rooms isolated from LMF. The study in [26] also implies an assumption that LMF may increase the blood vessel wall tone which is a negative factor for AMI. Data gathered during recent years encouraged us to perform this epidemiological analysis evaluating the causal links between changes in LMF and hospital admissions due to AMI in Lithuania from August 2014 till September 2019.

While analyzing the cardiovascular diseases associated with the LMF, it is imperative to recall the Earth's natural rhythm. The frequency of the earth's rhythm is 7.83 (Hz), known as the first "Schumann Resonance" with a (day/night) fluctuation of approximately ± 0.5 Hz. The higher frequencies include 14, 20, 26, 33, 39, and 45 (Hz), which all overlap with human brain rhythms, alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–100 Hz) [27,28]. In our study, we have analyzed the Schumann frequencies in the same ranges and used the letter S to indicate that we are referring to the Schumann frequencies (SDelta, δ (0–3.5 Hz), STheta, θ (3.5–7 Hz), SAlpha, α (7–15 Hz), SBeta, β (15–32 Hz) and SGamma, γ (32–65 Hz)) for the data.

As expounded upon in the preceding paragraphs, the correlation between LMF and AMI is pronounced [29]. In this study, it is hypothesized that there exists a long-term correlation between the LMF and AMI. The purpose of the study is to analyze the data gathered from two Lithuanian hospitals and the public health institute to determine the relationships between the LMF and the number of patients registered in hospitals with AMI. Furthermore, the work is unique in that the existence of the association between the AMI and LMF is observed across the lengthy period of the observation window, which would otherwise be overlooked when considering small observation windows. It could be possible that not all of the frequency ranges of the Schumann resonances contribute to defining the relationship between AMI and LMF. Therefore, finding the Schumann frequency ranges that tend to cause the AMI is also an important part of this study. The

research methods are based on extensive statistical analysis and the data are analyzed by the help of mathematical and statistical tools.

2. Methods

2.1. Ethics Statement

The research met all applicable standards for the ethics of experimentation in accordance with the Declaration of Helsinki as reflected in prior approval by the Regional Biomedical Research Ethics Committee of the Lithuanian University of Health Sciences (ID No. BE-2-21, 10 March 2021). Participants provided written informed consent prior to the experiment.

2.2. Data Collection and Categorization

Our team conducted a retrospective analysis of AMI cases in Lithuania from 1 August 2014 to 29 September 2019. The range of collected dataset is exactly 5 years, 1 month, 29 days. In the following paragraphs, there is a comprehensive description of the data classification. The measurement of the LMF and its explanation are also covered in more detail in the sections that follow.

2.3. Grouping of the Patients

The first group consists of all the patients who were diagnosed with an AMI event and were admitted to the Cardiology Department of University Hospital at Lithuanian University of Health Sciences. The second group is comprised of the patients who were diagnosed with an AMI event and were admitted to Siauliai Republic Hospital. The third group includes the statistical data about the morbidity of AMI, which are taken from the Institute of Hygiene in Lithuania.

2.4. Measurement of Local Magnetic Field

The LMF is measured with the Global Coherence Monitoring Network magnetometer, which is located in the Radviliskis area of Lithuania, near the town of Baisogala. A well-known group of spectrum peaks known as Schumann resonances are recorded as part of the experiment protocol. The measured Schumann resonances serve as the data to be analyzed in conjunction to the number of patients admitted to the hospital with AMI. The LMF can be measured in two directions, north/south and east/west. We have used the east/west detector for the LMF measurement [29]. The measurement procedure of the local magnetic field intensity is explicitly explained in the study [30,31]. The details of the different frequency ranges of the Schumann resonances are listed in Table 1.

Table 1. Description of the input X_n and output Y variables.

Variable	Different Frequency Ranges of the Schumann Resonance	Frequency Range (Hz)
X_1	SDelta (δ)	0–3.5
X_2	STheta (θ)	3.5–7
X_3	SAlpha (α)	7–15
X_4	SBeta (β)	15–32
X_5	SGamma (γ)	32–65
Y	The total number of patients hospitalized in Lithuania per day with the diagnosis of AMI	-

2.5. Grouping of Patient Data Based on Hospitals

As previously stated, the data are gathered from two hospitals and one public institute of health in Lithuania. The details of the hospitals and the public institute are as follows (1) Cardiology Department of University Hospital at Lithuanian University of Health Sciences, (2) Siauliai Republic Hospital, and (3) The Institute of Hygiene in Lithuania. The demographical categorization of the data is explained below.

2.5.1. First Group

A total of 918 patients were analyzed in the Cardiology Department of University Hospital at the Lithuanian University of Health Sciences. There were 429 males (46.7%) and 489 females (53.3%).

2.5.2. Second Group

A total of 548 patients were hospitalized in Siauliai Republic Hospital—324 males (59.1%) and 224 females (40.9%).

2.5.3. Third Group

Morbidity statistics are provided by the Lithuanian Institute of Hygiene. In total, 5917 patients had an AMI. A total of 3432 (58% of the patients) were male and 2485 (41%) were female. A total of 493 patients on average per month were hospitalized in Lithuania hospitals due to AMI within the described period.

The statistical approach, the governing model equations, the correlation between variables, and the time-average model are all explained in depth in the sections that follow.

3. Results

3.1. Description of the Statistical Analysis

Let us begin with presenting a brief overview of the input and output variables used in this study. The input variables are identified as X_n (where n varies from 1 to 5) and the output variable is denoted as Y . In Table 1, the variable X_n is the input parameter which describes the daily average of the Schumann resonances $S\Delta$, δ (0–3.5 Hz), $S\theta$, θ (3.5–7 Hz), $S\alpha$, α (7–15 Hz), $S\beta$, β (15–32 Hz) and $S\gamma$, γ (32–65 Hz). The variable Y is the output parameter and represents the total number of patients hospitalized per day (see Tables 1 and 2). In Figures 1–5, the x-axis shows the timeframe during which the recordings were made, which is from 2014 to 2019. The y-axis shows the daily averages of Schumann resonances observed for the local magnetic field. In Figure 6, the total number of patients hospitalized each day is shown.

Table 2. The first few records of the dataset with input variable X_n and the corresponding output variable Y with respect to the associated date.

Date	X_1	X_2	X_3	X_4	X_5	Y
1 August 2014	71.9816	32.8561	83.8413	104.1903	255.6396	11
2 August 2014	90.8082	48.7685	106.029	135.1208	274.8006	10
3 August 2014	108.8789	51.8121	95.4904	117.6708	249.9169	12
4 August 2014	94.6534	46.2272	86.5633	117.257	253.5175	11
5 August 2014	105.6558	67.4763	131.0236	196.8376	381.0183	14
...
29 September 2019	20.8557	17.5268	41.7625	61.4899	119.1067	13

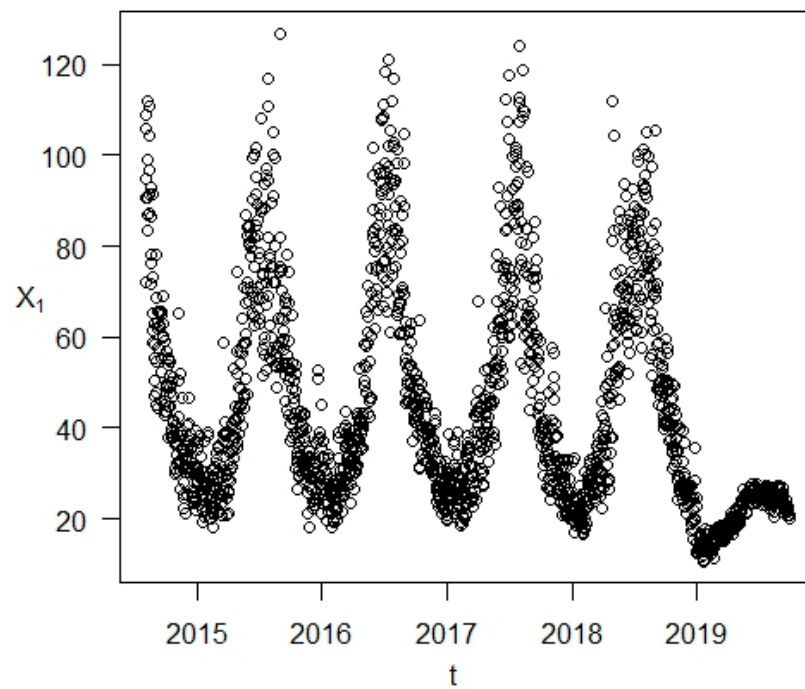


Figure 1. The monitoring data for the daily average of the δ frequency (0–3.5 Hz) for the local magnetic field measured in an east–west direction. The x-axis represents the time t , whereas the y-axis represents the parameter X_1 which is the SDelta band of the Schumann resonance.

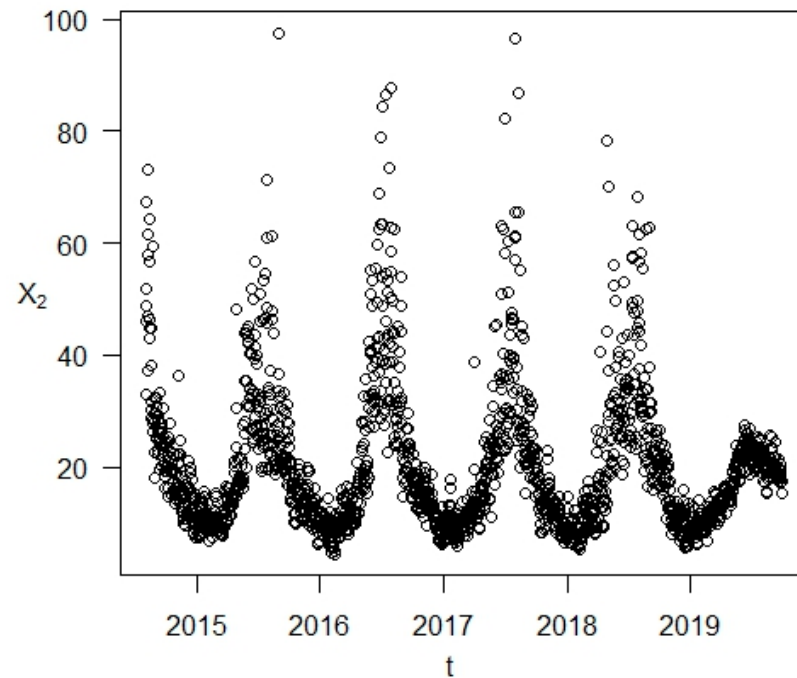


Figure 2. The monitoring data for the daily average of the θ frequency (3.5–7 Hz) for the local magnetic field measured in an east–west direction. The x-axis represents the time t , whereas the y-axis represents the parameter X_2 which is the STheta band of the Schumann resonance.

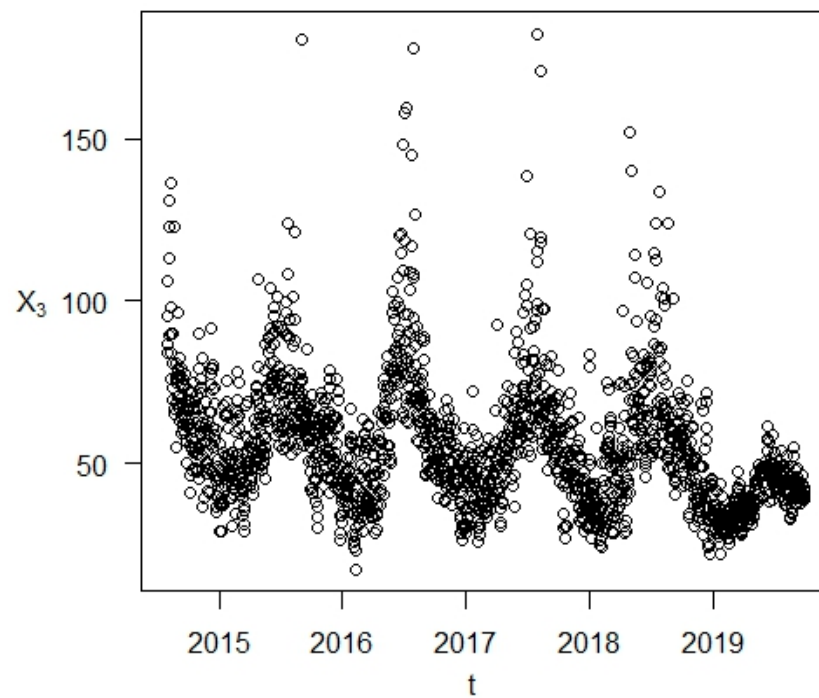


Figure 3. The monitoring data for the daily average of the α frequency (7–15 Hz) for the local magnetic field measured in an east–west direction. The x-axis represents the time t , whereas the y-axis represents the parameter X_3 which is the SAlpha band of the Schumann resonance.

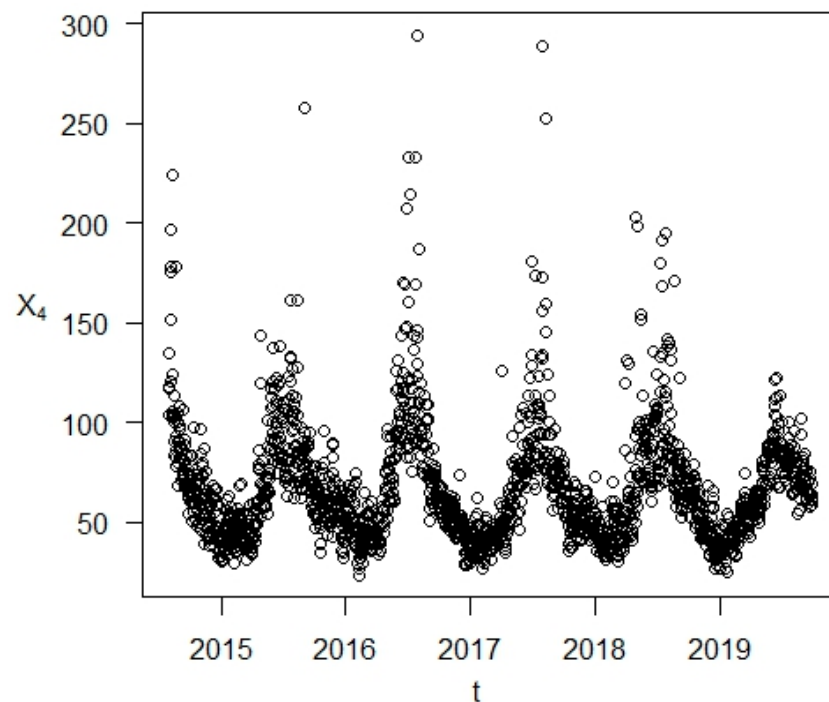


Figure 4. The monitoring data for the daily average of the β frequency (15–32 Hz) for the local magnetic field measured in an east–west direction. The x-axis represents the time t , whereas the y-axis represents the parameter X_4 which is the SBeta band of the Schumann resonance.

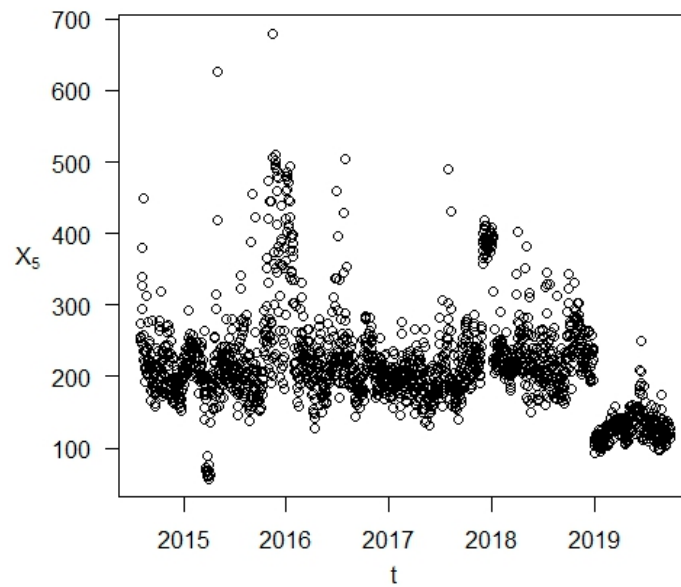


Figure 5. The monitoring data for the daily average of the γ frequency (32–65 Hz) for the local magnetic field measured in an east–west direction. The x-axis represents the time t which is the input variable, whereas the y-axis represents the parameter X_5 which is the SGamma band of the Schumann resonance.

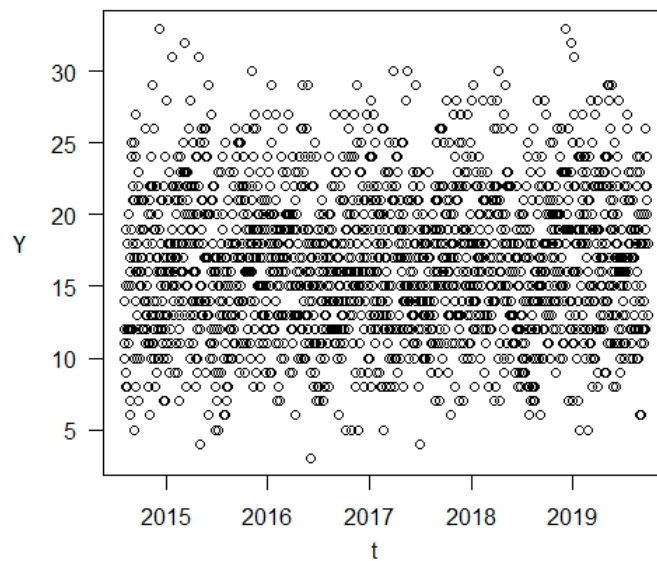


Figure 6. The total number of patients hospitalized per day with the diagnosis of AMI. The x-axis represents time (input parameter) whereas the y-axis represents the parameter Y (the output parameter which represents the total number of patients hospitalized in Lithuania per day with the diagnosis of AMI).

3.2. The Governing Model Equations and Explanations

The main objective of this study is to identify the relationship between Y (output) and $X_1, X_2, X_3, X_4,$ and X_5 (input) variables. To accomplish this task, statistical techniques are employed. The linear regression model is used to analyze the relationship between the input and the output variables. To begin with, the relationship between the output variable Y and the input X_n can be expressed as:

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + \varepsilon \tag{1}$$

where $b_0, b_1, b_2, b_3, b_4, b_5 \in \mathbb{R}$; ε is the residual of approximation; $\varepsilon \sim N(0, \sigma^2)$.

Let us denote the observable values of Y as y_1, y_2, \dots, y_n , where n is the number of days available in the dataset. The considered linear regression model then reads:

$$y_i = b_0 + b_1x_{i1} + b_2x_{i2} + b_3x_{i3} + b_4x_{i4} + b_5x_{i5} + \varepsilon_i \tag{2}$$

where x_{ij} is the i -th observation of variable X_j ($j = 1, 2, \dots, 5$); ε_i is the i -th residual ($i = 1, 2, \dots, n$). The model can be expressed in matrix form:

$$Y = XB + \varepsilon \tag{3}$$

where $Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}$, $X = \begin{pmatrix} 1 & x_{11} & x_{12} & \dots & x_{15} \\ 1 & x_{21} & x_{22} & \dots & x_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & \dots & x_{n5} \end{pmatrix}$, $B = \begin{pmatrix} b_0 \\ b_1 \\ \vdots \\ b_5 \end{pmatrix}$, $\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$.

The vector of model parameters B are determined by the method of least squares:

$$\hat{B} = (X^T X)^{-1} X^T Y \tag{4}$$

Following this, the regression equation reads:

$$\hat{Y} = X \hat{B} \tag{5}$$

3.3. Correlations between Input Variables X_1, X_2, X_3, X_4 , and X_5

The model of the multi-parameter linear regression is valid when variables X_1, X_2, X_3, X_4 , and X_5 do not correlate in pairs. This condition is validated by computing Pearson correlation coefficients between the variables:

$$r_{X_i X_j} = \frac{\sum_{k=1}^n (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)}{\sqrt{\sum_{k=1}^n (x_{ki} - \bar{x}_i)^2 \sum_{k=1}^n (x_{kj} - \bar{x}_j)^2}} \tag{6}$$

where $\bar{x}_i = \frac{1}{n} \sum_{k=1}^n x_{ki}$. The computational results are presented in Table 3.

Table 3. Pearson correlation coefficients between variables X_1, X_2, X_3, X_4, X_5 .

$r_{X_i X_j}$	X_1	X_2	X_3	X_4	X_5
X_1	1	0.90	0.84	0.79	0.20
X_2	0.90	1	0.90	0.95	0.16
X_3	0.84	0.90	1	0.90	0.32
X_4	0.79	0.95	0.90	1	0.26
X_5	0.20	0.16	0.32	0.26	1

From Table 3, it can be observed that variables X_1, X_2, X_3, X_4 are linked by a strong positive linear relationship. However, relationships between X_5 and X_1, X_2, X_3, X_4 are weak. According to the hypothesis test, the correlation value between the variables is equal to zero and they are rejected with a significance level (p -value) < 0.05 . Therefore, the Pearson correlation coefficients are statistically significant. The three regression equations listed in Table 4 describe the relationship between the input variables.

Table 4. Equations defining the relationship between the input variables.

Formula (1)	Formula (2)	Formula (3)
$\hat{x}_2 = -1.26 + 0.49x_1$ ($R^2 \approx 0.8$)	$\hat{x}_3 = 24.32 + 0.71x_1$ ($R^2 \approx 0.71$)	$\hat{x}_4 = 24.17 + 0.98x_1$ ($R^2 \approx 0.63$)

The null hypothesis about the coefficients being equal to zero is rejected with a significance level (p -value) of <0.05 . Therefore, the alternative hypothesis that the model coefficients do not equal zero is accepted. The hypotheses about the equality of model coefficients with zero are dropped with a significance level (p -value) of <0.05 . Thus, the model coefficients statistically significantly differ from zero. Therefore, some of the variables X_1, X_2, X_3, X_4 must be dropped from the regression equation because those variables are multi-colinear, and those correlations are strong. After dropping the variables $X_2, X_3,$ and X_4 , the regression equations reads.

$$Y = b_0 + b_1X_1 + b_2X_5 + \varepsilon \tag{7}$$

3.4. The Time-Average Model

It appears that the instantaneous relationship between variables Y and X_1 and X_5 is insignificant. The linear regression model (Equation (7)) yields insignificant coefficients, and the coefficient of determination is very small. However, it would be strange to expect to observe an instantaneous causal relationship between the local magnetic field and the number of hospitalized patients with myocardial infarction. Otherwise, one could expect to observe a sharp increase in the number of myocardial infarctions at the day of the increased geomagnetic activity. However, such relationships have not been reported (our study also does not reveal instantaneous relationships between the local magnetic field and the number of infarctions).

In this work, the influence of the averaged magnetic field on the individuals experiencing the heart attack becomes evident over long observation windows [32]. One could consider the well-known effect of nonlinear chaotic synchronization. For example, the magnitude of the diffusive coupling between two chaotic oscillators can be below the noise level—but chaotic synchronization can be detected between two (or more) coupled nonlinear oscillators after long transients. A paradigmatic example of such coupled systems is the synchronization of Huygens pendulum clocks discovered more than 300 years ago [33], but still studied in scientific literature today [34,35].

Keeping such small possible interactions in mind, we transform the governing regression equation model (Equation (7)) into a time-average regression model. The instantaneous (24-h based values) are replaced by their overlapping moving averages. The length of the observation window used for the averaging L is set to 90, 120, and 180 days.

For example, the least squares method for the regression model (Equation (7)) yields the following estimates of the model parameters at $L = 180$:

$$\hat{B} = \begin{pmatrix} 18.0921 \\ -0.0314 \\ -0.0004 \end{pmatrix}$$

The following hypothesis is tested with the significance level $\alpha = 0.05$:

$$\begin{cases} H_0 : b_0 = b_1 = b_2 = 0, \\ H_a : \text{at least one } b_i \text{ (} i = 0, 1, 2 \text{) is not equal to zero.} \end{cases}$$

Additionally, hypotheses about the equality of individual coefficients with zero are tested separately:

$$\begin{cases} H_0 : b_k = 0, \\ H_a : b_k \neq 0. \end{cases} \quad k = 0, 1, 2.$$

In all cases, the main hypotheses H_0 are rejected (p -value < 0.05). Therefore, the coefficients of the regression equation b_0, b_1, b_2 differ significantly from zero. The results of hypothesis testing and parameter estimates are given in Table 5.

Table 5. Results of hypothesis testing and parameter estimates.

Coefficients	Estimate	Std. Error	t Value	Pr(T > t)
Intercept	18.0920587	0.0412784	438.294	$<2 \times 10^{-16}$
X_1	-0.0313948	0.0004666	-67.281	$<2 \times 10^{-16}$
X_5	-0.0004143	0.0001872	-2.213	0.0271

In Table 5, the R^2 value is 0.744 and $R^2_{adjusted}$ value is 0.7437. The F-statistics are 2474 and 1702 degrees of freedom, and the p -value is less than $2.2e^{-16}$.

3.5. The Derived Model and Statistical Estimates

The derived regression equation with 180-day moving averaging interval reads:

$$\hat{y} = 18.0921 - 0.0314x_1 - 0.0004x_5$$

The variation intervals of variable x_1 is [18.5;68.3] and x_5 is [131.2;297.2] accordingly. The suitability of the model and special variants of this model are discussed in this subsection.

The variance inflation factor (VIF) is computed for each variable. $VIF = 1.0734 < 4$ for both variables X_1 and X_5 . Therefore, those variables are not multi-collinear (see Table 6).

Table 6. Variance inflation factor (VIF) is computed for each variable.

Variable	VIF	Detection *
X_1	1.0734	0
X_5	1.0734	0

* 0-collinearity is not detected by the test.

In Table 6, the 0-multicollinearity criterion marks that the quantities are not multi-collinear. Multicollinearity is a statistical phenomenon that occurs when two or more independent variables in a regression model are highly correlated with each other. In other words, multicollinearity indicates a strong linear relationship among the predictor variables. It is possible that the pairwise correlations are small, and yet a linear dependence exists among three or even more variables, for example, if $X_3 = 3X_1 + 2X_2 + \text{error}$.

If $VIF < 4$ for some variable (in this case, the criterion acquires a value/mark of 0), it means that the variable is not correlated or weakly correlated with other variables, so it is appropriate to include this variable in the regression model.

The determination coefficient of the time-averaged model ($L = 180$) is $R^2 \approx 0.74$. Therefore, the moving averages of X_1 and X_5 well describe the variation in the moving average of Y (see also Figure 7).

The limitation of the derived model is that the residual errors are not distributed according to the normal distribution. However, this distribution is close to normal. Therefore, it is likely that the problem would vanish if the number of observations n were enlarged.

The time-average model at $L = 90$ reads:

$$\hat{y} = 18.0339 - 0.0333x_1$$

The time-average model at $L = 120$ reads:

$$\hat{y} = 18.0526 - 0.0326x_1$$

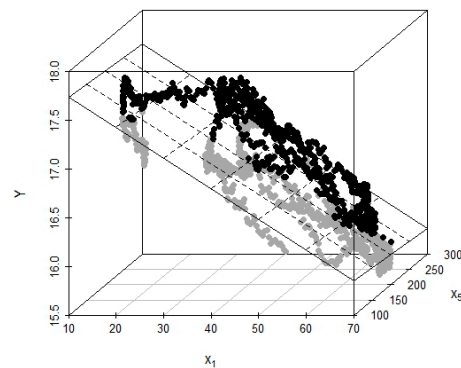


Figure 7. The regression plane is plotted for the time-average model for parameters X_1 , X_5 , and Y . The points above the plane are represented in black, whereas the points below the plane are represented in gray.

In both cases, the coefficient at X_5 does not differ significantly from zero. Other coefficients do differ significantly from zero ($\alpha = 0.05$). The determination coefficient at $L = 90$ is 0.6. The determination coefficient at $L = 120$ is 0.66. Those results prove that the best linear regression model is derived at $L = 180$.

The time-average model at $L = 180$ is derived by dropping the variables X_2 , X_3 , and X_4 . The model can be constructed by dropping other sets of multi-colinear variables.

The time-average model with dropped variables X_1 , X_3 , X_4 at $L = 180$ reads.

$$\hat{y} = 18.7404 - 0.0675x_2 - 0.0037x_5$$

and the determination coefficient of the model is 0.72.

Dropping variables X_1 , X_2 , X_4 yields the time-average model ($L = 180$).

$$\hat{y} = 19.3244 - 0.0477x_3$$

However, variable X_5 becomes statistically insignificant in this model. The determination coefficient of the model is 0.75.

Finally, dropping X_1 , X_2 , X_3 yields the time-average model ($L = 180$).

$$\hat{y} = 19.44 - 0.0307x_4 - 0.0037x_5$$

The determination coefficient of this model is 0.66.

4. Discussion

As mentioned before, the purpose of the study is to find the long-term relationship between the LMF and the AMI. To achieve the objective, the patients are investigated by the variations of Schumann resonance namely (SDelta (0–3.5 Hz), STheta (3.5–7 Hz), SAlpha (7–15 Hz), SBeta (15–32 Hz) and SGamma (32–65 Hz). The Schumann resonances as well as the number of AMI patients registered in each of the hospitals are recorded each day. The output (Y) represents the total number of patients hospitalized in Lithuania per day with the diagnosis of AMI. The input variable X_1 , X_2 , X_3 , X_4 and X_5 represents the daily averages of the Schuman resonance ($\delta, \theta, \alpha, \beta, \gamma$) for the LMF measured by the Lithuanian magnetometer. First, the linear regression model equation is posed in (Equation (1)) to show the relationship between the input and output variables. The observable values of the output variable Y reads y_1, y_2, \dots, y_n , so (Equation (1)) translates to (Equation (2)). For convenience, the matrix form of the same is also presented in (Equations (3)–(5)). The proposed model of linear regression is based upon multi-parameters (due to having different Schumann resonances and number of patients registered each day). Therefore, the validity of the multiparameter model in linear regression is proved by computing the Pearson correlation coefficients between the input variables X_1 , X_2 , X_3 , X_4 and X_5 . The

typical condition for adhering to the multi-parameter linear regression is “the variables should not correlate in pairs”. Theoretically, this means finding out Schumann resonance which have a weak relationship in pairs. The results of Table 3 indicate that the variables X_5 and X_1, X_2, X_3, X_4 are weak in their relationship under the significance level of 0.05. This step provides a lead in formulating the equations that describe the relation between variables $(x_1, x_2), (x_1, x_3)$ and (x_1, x_4) . However, the hypothesis about the equality of model coefficients to zero is dropped, with a significance level 0.05 (p -value < 0.05). Some of the variables, X_1, X_2, X_3, X_4 , must be dropped from the regression equation because these variables are multi-colinear, and correlations are strong. After dropping the variables X_2, X_3 , and X_4 , the regression equations reads (Equation (7)). However, (Equation (7)) produces results which are based upon the data which are observed for short term scales, or in other words; the linear regression model presented in (Equation (7)) yields statistically insignificant coefficients, and the coefficient of determination is very small.

This raises the question: Does the linear regression model in (Equation (7)) provide enough information to determine the relationship between AMI and LMF? To answer the question, it can be stated that (Equation (7)) happens to represent the instantaneous causal relationship between the LMF and the number of hospitalized patients with AMI. This demonstrates that a rise in geomagnetic activity will likewise increase the number of individuals experiencing heart attacks, which is not possible.

As a result, the paucity of instantaneous correlations leads to the necessity to investigate the long-term relationship between AMI and LMF. Therefore, we transformed the governing equations to a time-averaged regression model, which is the essence of the study. The averages of the relevant Schumann resonances $SBeta$ (15–32 Hz) and $SGamma$ (32–65 Hz) influence the average number of patients.

To shed light upon the various causes of AMI, it is reasonable to ponder whether the LMF is the only cause of AMI. Again, the subject is vast and must be investigated from other perspectives. AMI can perhaps also be due to trauma, excess demand on the heart, etc. Additionally, the origin and the description of the pathomechanisms of this relationship are out of the scope of this study. Detailed investigations of causes, origins, and mechanisms involved remain a definite aim of future research. The study’s main objective is to prove the statistical hypothesis on the existence of long-term relationships between LMF and the number of hospitalized patients with the symptoms of AMI.

5. Conclusions

The study’s findings revealed significant long-term relations between LMF and AMI. Furthermore, it has been demonstrated that not all of the Schumann resonances contribute to having an impact on individuals developing AMI. For example, the Schumann resonances from the $SBeta$ (15–32 Hz) and $SGamma$ (32–65 Hz) have been shown to play an important role in determining long-term relationships. It is also part of the study’s conclusion that the instantaneous relationships observed between geomagnetic variations and AMI patients are not significant.

6. Limitations

This research study comes with limitations similar to any other scientific work. The first constraint is that only data from individuals who have been diagnosed with AMI and admitted to the hospital were collected. It is probable that there might be cases who have developed the symptoms of AMI but have not been admitted to the hospitals. In other words, off-the-record data are not taken into account.

Another limitation of the study is pertinent to the derived model of the study. It is observed that with a derived model, the residual errors are not distributed according to the normal distribution, although they might be close to the normal. Therefore, it is likely that the problem would vanish if the number of observations were enlarged.

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Nomenclature

AMI	Acute myocardial infarction
LMF	Local earth magnetic field
GS	Geomagnetic storms
HRV	Heart rhythm variability
EEG	Electroencephalogram

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