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RESEARCH ARTICLE

THE REGRESSIVE OBJECTIVE REGRESSION METHOD AND ITS INCIDENCE IN THE MATHEMATICAL MODELATION OF CHOLERA IN CAIBARIEN, VILLA CLARA, CUBA

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ABSTRACT

The objective of this research was to model a series of data about the number of people with cholera in six People councils of Caibarién municipality, corresponding to years 2013 and 2014. Also, to determine which model best explains the variance of this disease. The Regressive Objective Regression Methodology was used with two alternatives: the first corresponds to the use of a short-term modeling (model1) and the second, based on a modeling with climatic variables only. It was obtained that model 1 presents minor errors and explained variance, greater than model 2. The tendency of the series in the Popular Council 1 was not of significant increase, Humidity and Precipitation were not significant. A 4-month regressive parameter on the impact of cholera is presented, which coincides with previous work on acute respiratory infections. In relation to cholera trend, this variable has a 4-month regressive parameter, which coincides with the impact of El Niño phenomenon. It is concluded that model 1 is the one with the best results with the least errors and the highest explained variance and statistical regularity is the philosophical principle on which the regressive methodology is based.

INTRODUCTION

The information in a series of data is important when it comes to projecting the future, but what happens when the series to be modeled is a white noise?, and therefore, there is no information in previous steps that allow us to model towards the future, in this article we will discuss the Regressive Objective Regression (hereinafter referred to as ROR) Methodology and how through it should be obtained important information to project the future behavior of the series (Osés and Grau, 2011; Osés *et al*., 2015). The ROR Methodology is performed in several steps, which are explained in this article. That is why, we believe necessary to detail them in this work from the mathematical point of view (Osés and Grau, 2011). In this methodology an adjustment of curves is made using the least squares method which we will explain next.

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It is often necessary to represent data that has been given as a set of X-Y points, through a functional relationship. It is supposed, for example, that we have done some experiments and have obtained the points X - Y plotted in a graph of Y against X. Since these points are going to be used for computer calculations, we face several problems.

- There are experimental errors in Y values. We would like to soften in some way the variations due to experimental errors.
- We may wish to know the Y value of corresponding to some X value that lies between two experimental X values.
- It would be desirable - in fact it may be the main purpose of the calculation - to extrapolate, i.e. to determine the Y value that corresponds to an X value of outside the range of experimental values of this variable.

All of these considerations lead us to the need for a functional relationship between X and Y in the form of an equation and we expect it to be simple. The question then is to determine a curve that approximates the data with sufficient precision. The first question presented is: How will we decide if a given curve is a good "fit" to the data? This discussion will be easier if we define a new term now. The deviation at a given point is the difference between the experimental Y value and the Y value calculated from a functional relationship.

That is why, the question of adjusting a curve to the data can be reformulated: what condition must be put on the deviations to arrive at an adequate curve? One possibility that might seem attractive is to ask that the sum of the deviations be as small as possible. If we use a premium to identify the values of Y, calculated from the sought functional relationship, this means asking for a minimum, in which N is the number of data points but the attractiveness of this possibility disappears when we consider the simple case of adjusting a line to two points. We could avoid this difficulty by specifying absolute values, that is, by requiring minimization (McCracken& Dorn, 1971).

$$\sum_{i=1}^{N} (Y_i - Y_i')$$

$$\sum_{i=1}^{N} I\, Y_i - Y_i' I$$

But we cannot derive to find a minimum value, because the absolute value function has no derivative in its minimum. We could think of asking that the maximum error be a minimum, which is the Chebyshev approximation. Nevertheless, this leads to a complicated iterative process to determine the functional relationship. We thus arrive at the criterion of least squares, in which a minimum value of:

$$\sum_{i=1}^{N} (Y_i - Y_i')^2$$

As we can see, this expression can be differentiated to determine its minimum, leading to equations, which are linear in many cases of practical interest, and which, in principle, are easy to solve. Finally, there are statistical considerations that suggest the criterion of least squares is a good criterion; in addition, of its computing facility. We then write the approximation function for the ROR Methodology as:

$$Y_i' = c_1 * \delta_1 (xi) + c_2 * \delta_2 (xi) + c_3 * \mathbf{NoC}(xi).$$

Where:

$$\delta_1(xi) = \begin{cases} 0 & \text{si } Xi = 2n \\ 1 & \text{si } Xi = 2n+1. \end{cases} \quad n= 0,1\ldots N$$

$$\delta_2(xi) = \begin{cases} 1 & \text{si } Xi = 2n \\ 0 & \text{si } Xi = 2n+1. \end{cases} \quad n= 0,1\ldots N$$

NoC(xi) = xi , xi = 0,1,…, N.

The objective is to determine C1, C2 and C3, such to minimize:

$$S= \sum_{i=1}^{N} (Y_i - Y_i')^2$$

$$S= \sum_{i=1}^{N} (Y_i - c_1 * \delta_1(xi) - c_2 * \delta_2 (xi) - c_3 * \mathbf{NoC}(xi)^2$$

We know that minimizing S considered as a function of C1, is to make the partial derivative of S equal to zero with respect to C1, where the result is:

$$(\partial S/\partial c_1)= (-2)\sum_{i=1} (Y_i - c_1 * \delta_1(xi) - c_2 * \delta_2 (xi) - c_3 * \mathbf{NoC}(xi) =0.$$

Doing equal to zero and reordering, we obtain:

$$c_1 * (\sum_{i=1}^{N} \delta_1 (xi)) + c_2 * (\sum_{i=1}^{N} \delta_2 (xi)) + c_3 * (\sum_{i=1}^{N} \mathbf{NoC}(xi)) = \sum_{i=1}^{N} Yi.$$

$$c_1 * (\begin{smallmatrix}0\\N\end{smallmatrix}) + c_2 * (\begin{smallmatrix}N\\0\end{smallmatrix}) + c_3 * (\sum_{i=1}^{N}(xi)) = \sum_{i=1}^{N} Yi.$$

Deriving S with respect to C2 and then with respect to C3 and making each of the results equal to zero, we obtain two more equations in the unknowns C1, C2, C3, the three simultaneous equations in these three unknowns are called normal equations to fit an equation to the data set, then:

$$c_1 * (\begin{smallmatrix}0\\N\end{smallmatrix}) + c_2 * (\begin{smallmatrix}N\\0\end{smallmatrix}) + c_3 * (\sum_{i=1}^{N}(xi)) = \sum_{i=1}^{N} Yi.$$

$$c_1 * (\begin{smallmatrix}0\\N\end{smallmatrix}) + c_2 * (\begin{smallmatrix}N\\0\end{smallmatrix}) + c_3 * (\sum_{i=1}^{N}(xi)) = \sum_{i=1}^{N} Yi.$$

$$c_1 * (\begin{smallmatrix}0\\N\end{smallmatrix}) + c_2 * (\begin{smallmatrix}N\\0\end{smallmatrix}) + c_3 * (\sum_{i=1}^{N}(xi)) = \sum_{i=1}^{N} Yi.$$

To find our "best" function for the data; we only need to carry out the necessary sums and solve the system of three equations, this combination explains a great amount of variance of Yi then we get:

$$Y_i' = c_1 * \delta_1 (xi) + c_2 * \delta_2 (xi) + c_3 * \mathbf{NoC}(xi).$$

So, the errors = (Yi - Yi ') so we calculate the cross correlation of ei with Yi-n (xi) in the following formula:

$$\mathrm{Corr}(ei, Y_{i-n}(xi)) = \frac{\mathrm{Cov}(ei, Y_{i-n}(xi))}{[\mathrm{Var}\,(ei)*\mathrm{Var}\,(Y_{i-n}(xi)]^{1/2}}$$

and we choose the maximum value of

That function is the corresponding peak called t then calculate the variable Yt and solve the system again this time with the variable Yt,

$(\partial ei / \partial ci) = (\partial S2 / \partial ci) = 0$ this time with the function:

S2 = (Yi - c1 * δ 1 (xi) - c2 * δ 2 (xi) - c3 * NoC (xi) -c4 * Yt (xi)) 2, Then we have an error e2 that correlates it with g**ik** (xi) as an exogenous variable, as it was done with **ei** obtaining a new peak in **t** for the variable g ik (xi), and we solve the system again, (t it can be of order different from that calculated for the function Yi-n (xi). This time (∂ei / ∂ci) = (∂S3 / ∂ci) = 0 in such a way that.

S3 = (Yi - c1 * δ 1 (xi) - c2 * δ 2 (xi) - c3 * NoC (xi) -c4 * Yt (xi) -c5 * g t (xi)) 2,

We obtain at the end an error e4 that must have zero mean and variance 1 and stop the process obtaining the greatest amount of explained variance possible, in this approximation we use data of the same function Yi-n (xi) and exogenous data of the function g ik (xi). This methodology was used in a model for the variable angiostrongilosis (Osés and Fimia, 2012), where the following function model was obtained:

Table. Obtained Model for Angiostrongilosis disease

Coefficients[a,b]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	DI	-981.340	308.741	-1.381	-3.179	.003
	DS	-795.908	304.288	-1.120	-2.616	.013
	NoC	7.166	3.007	.374	2.383	.023
	Lag3angiostot	.880	.190	.719	4.630	.000
	Lag3XY1	33.632	12.277	1.626	2.739	.010

a. Dependent Variable: Angiostotal

b. Linear Regression through the Origin

Where DS = δ1 (xi) and DI = δ 2 (xi) NoC = NoC (xi), it is the trend and Lag3angiostot = Yi-n (xi) is the angiostrongilosis returned in three bimesters (t = 3) and lag3XY1 is the exogenous variable Average Temperature in the Yabu station (g ik (xi) returned in three bimesters where t equals 3, as for angiostrongilosis. The ROR methodology has been widely used (Osés and Grau, 2011), but the methodology of Box *et al.* (1994) will not be used, since it has limitations (Osés and Grau, 2011), we use the version of the SPSS version 13 package. The ROR methodology has also been used for the forecast of high intensity earthquakes in Cuba (Osés *et al.*, 2012a); in addition, for the monitoring and control of mosquitoes (Fimia *et al.*, 2012a). Their results have been used in the study of climate change and health in Villa Clara Cuba (Osés *et al.*, 2012b), these mathematical models were applied to the infectious entity Malaria (Fimia *et al.*, 2012b). The ROR methodology was also applied in Meteorology, in the modeling of cold fronts and the impact of sunspots (Osés *et al.*, 2012c). Likewise, it has been used for the prediction of the larval density of Anopheles mosquitoes and in the realization of long-term forecasts (Osés *et al.*, 2012d; Osés *et al.*, 2014), one year in advance for meteorological variables. The ROR methodology opens a wide range of possibilities for its use. The objective of the research was to model the data series for the number of patients with cholera in six Popular Councils of Caibarién municipality, Villa Clara province, during the years 2013 and 2014, as well as to determine which model best explains the variance of this parameter.

MATERIALS AND METHODS

A series of month data were used on the number of patients with cholera corresponding to six Popular Councils in Caibarien municipality, Villa Clara province, Cuba, included in the period of 2013 and 2014. The ROR methodology was used with two alternatives: the first, corresponds to the use of a short-term modeling (model1) and the second, using a modeling with climatic variables only. In the ROR methodology, the variables Sawtooth (DS) and Inverted Saw Tooth (ID), represent the ups and downs of the series, while NoC (Number of cases), represents its trend. So that, DS and DI take alternate values of zero and one, which represents two states. The monthly data were taken from the historical archive of the Climate Department of the Provincial Meteorological Center of Villa Clara, Cuba. The correlations were analyzed with seven climatic variables taken from the meteorological station of Caibarién, these are:

- Maximum Temperatures (Tmax)
- Minimum Temperatures (Tmin)
- Average Temperatures (Tmed)
- Maximum Relative Humidity (HRmax)
- Minimum Relative Humidity (HRmin)
- Relative Medium Humidity (HRmed)
- Precipitation (Prec)

RESULTS AND DISCUSSION

Six popular councils were analyzed, showing the correlations that were significant for each council. In Popular Council 1, three temperatures were significant at 95%, as the temperature increases cholera cases (table 1), these results coincide in the same way to other infectious entities with the ROR methodology (Cepero *et al*., 2013; Fimia *et al*., 2014a; Osés *et al*., 2015).

Table 1. Correlation between temperatures and cholera in Popular Council 1

Correlations

		Tmed	Tmax	Tmin	CP_1
Tmed	Pearson Correlation	1	.961**	.965**	.520*
	Sig. (2-tailed)		.000	.000	.013
	N	22	22	22	22
Tmax	Pearson Correlation	.961**	1	.864**	.531*
	Sig. (2-tailed)	.000		.000	.011
	N	22	22	22	22
Tmin	Pearson Correlation	.965**	.864**	1	.463*
	Sig. (2-tailed)	.000	.000		.030
	N	22	22	22	22
CP_1	Pearson Correlation	.520*	.531*	.463*	1
	Sig. (2-tailed)	.013	.011	.030	
	N	22	22	22	24

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

In Popular Councils 2, 4 and 5 the climatic variables were not significant. In Popular Council 3, temperatures were positively significant at 95%. As the temperatures increase, cholera cases increases too, the same as in Popular Council 1, which is shown in table 2. These results agree with works carried out in previous years by other authors (Fimia *et al*., 2014a; Fimia *et al*., 2015; Osés *et al*., 2016). In the case of Popular Council 6, only the minimum temperature was negatively significant at 95%.

As the minimum temperature increases, cholera cases decrease, in this People Council there are many cases with zero value in different months. With regard to precipitation and humidity, no significant correlations were observed in the data, perhaps this is due to the fact that these variables have a greater variability and need a longer series in order to express their impact (Fimia *et al*., 2015; Fimia *et al*., 2016; Osés *et al*., 2017a).

Table 2. Correlations between temperatures and cholera in Popular Council 3

Correlations

		Tmed	Tmax	Tmin	CP_3
Tmed	Pearson Correlation	1	.961**	.965**	.506*
	Sig. (2-tailed)		.000	.000	.016
	N	22	22	22	22
Tmax	Pearson Correlation	.961**	1	.864**	.436*
	Sig. (2-tailed)	.000		.000	.042
	N	22	22	22	22
Tmin	Pearson Correlation	.965**	.864**	1	.477*
	Sig. (2-tailed)	.000	.000		.025
	N	22	22	22	22
CP_3	Pearson Correlation	.506*	.436*	.477*	1
	Sig. (2-tailed)	.016	.042	.025	
	N	22	22	22	24

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 3. Minimum temperature and cholera correlations in Popular Council 6

Correlations

		Tmin	CP_6
Tmin	Pearson Correlation	1	-.425*
	Sig. (2-tailed)		.049
	N	22	22
CP_6	Pearson Correlation	-.425*	1
	Sig. (2-tailed)	.049	
	N	22	24

*. Correlation is significant at the 0.05 level (2-tailed).

Below we present the results of the ROR modeling for the short-term model 1 using the variables DS, DI and NoC (table 4). As it is appreciated, the explained variance R is 0.759, with an error of 4.26 cases. The Durbin Watson indicates the existence of correlation in errors, that´s the reason why more information of variables is needed. So that this parameter is close to two and we will introduce later the Lag variables or more significant delays.

Table 4. Summary of the short-term model 1 Popular Council 1

Model Summary[c,d]

Model	R	R Square[a]	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.759[b]	.576	.435	4.26580	1.796

a. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared to R Square for models which include an intercept.

b. Predictors: Lag4Tmax, Lag4CP_1, DS, NoC, DI

c. Dependent Variable: CP_1

d. Linear Regression through the Origin

The model is significant, with a Fisher's F of 4,078, significant at 99% (table 5).

Table 5. Analysis of Cholera Variance in the People Council 1

ANOVA[c,d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	371.045	5	74.209	4.078	.015[a]
	Residual	272.955	15	18.197		
	Total	644.000[b]	20			

a. Predictors: Lag4Tmax, Lag4CP_1, DS, NoC, DI

b. This total sum of squares is not corrected for the constant because the constant is zero for regression through the origin.

c. Dependent Variable: CP_1

d. Linear Regression through the Origin

Model 1 (Table 6) shows a non-significant increase trend in short term (0.267), it is observed that almost all variables are significant.

The model depends on Lag4 in People Counsel 1. That is, the amount of cholera returned in 4 months, as well as the maximum temperature returned in 4 months (Lag4 Tmax). That provides variance, that is why we left it in the model, these results coincide with the period of 4 months which is important in acute respiratory diseases and the typical El Niño phenomenon (Osés *et al*., 2003; Pérez *et al*., 2017; Aldaz *et al*., 2017).

Table 6. Short-term model 1. People Council 1

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	DS	-28.577	18.957	-3.561	-1.507	.152
	DI	-33.174	19.804	-4.134	-1.675	.115
	NoC	.267	.185	.735	1.443	.169
	Lag4CP_1	-.865	.307	-.698	-2.821	.013
	Lag4Tmax	1.096	.689	5.641	1.590	.133

a. Dependent Variable: CP_1

b. Linear Regression through the Origin

We proceeded to modeling only with climatic variables or model 2, the result (table 7) has explained variance R adjusted, of 0.532, with an error of 4.8. With respect to model 1, this error is greater and the R is smaller, so we can consider that model 1 presents better results than model 2 with pure climatic variables, these results that agree with Aldaz *et al*. (2017), Osés *et al*. (2017a) and Osés *et al*. (2017c).

Table 7. Summary of model 2 with People Council 1

Model Summary[c,d]

Model	R	R Square[a]	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.532[b]	.283	.212	4.80401	1.547

a. For regression through the origin (the no-intercept model), R Square measures the proportion of the variability in the dependent variable about the origin explained by regression. This CANNOT be compared t R Square for models which include an intercept.

b. Predictors: Tmin, Tmax

c. Dependent Variable: CP_1

d. Linear Regression through the Origin

In table 8 the variables Tmax and Tminare shown, although they are included in the model, they are not significant. Finally, we present the real value and forecasts with model 1, predicted by ROR and model 2, with pure climatic variables (figure 1).

Table 8. Model 2 with climatic variables in Popular Council 1

Coefficients[a,b]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	Tmax	-.067	.943	-.364	-.071	.944
	Tmin	.221	1.259	.896	.175	.863

a. Dependent Variable: CP_1

b. Linear Regression through the Origin

It is appreciated that model 2 (predicted by ROR) explains little variability in relation to model 1. The figure shows how model 1 best shows the variability of cholera in this popular council.

Table 9. Variables excluded in model 2 with pure climatic variables

Excluded Variables[b,c]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Tmed	15.073[a]	.349	.731	.080	2.01E-005

a. Predictors in the Model: Tmin, Tmax

b. Dependent Variable: CP_1

c. Linear Regression through the Origin

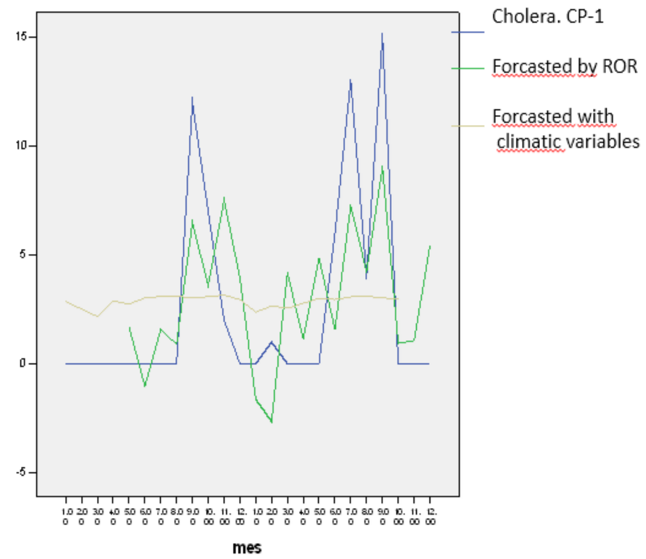

Figure 1. Cholera in Popular Council 1 and value predicted by ROR with pure climatic variables

There is a tendency to increase cases for the end of the series, as the real data were null, it can be described as successful preventive measures taken to cut the disease. We want to point out in this paper, that ROR methodology is based on a philosophical principle, which is statistical regular. This is a form of causal relationships, where a given state of the system does not univalent determine all subsequent states, but rather with a certain degree of probability, which is the objective to measure the possibility of realizing the trends of change that have appeared in the past (Fimia *et al*., 2014b; Osés *et al*., 2017c). Statistical regularity applies to all non-autonomous systems that depend on constantly changing external conditions and have a very large number of elements. On the other hand, dynamic regularity acts in all autonomous systems, which depend on external effects and have a sufficiently small number of elements, as it is, the character of the displacement of the planets in the solar system (Rosental & Iudin, 1981).

The difference between R.e and R.d is relative, since all dynamic regularity is statistical regular, with the probability of realization of events close to one. This is because every material system is inexhaustible, consists of a number of elements, has various external connections and changes qualitatively over time; it is for this reason that we can project the state of future systems based on past states of that system (Osés *et al*., 2015; Aldaz *et al*., 2017; Osés *et al*., 2017b). It is concluded that model 1 presents minor errors and explains variance greater than model 2. The tendency of the series in Popular Council 1 was to the non-significant increase and a 4-month regression parameter was presented in the impact of cholera, which coincides with previous work on acute respiratory infections.

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