Approaching Mean Air Temperature-Rainfall Models by Means of Genetic Programming under Climatic Change Scenarios

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Abstract: *The study of how climatological variables had been or will change over time under emissions of greenhouse gases, has been the subject of several researches since the late nineteenth century and they have increased since the eighties of the XXI Century. The population growth in the medium and short term means a greater urbanization with the consequent change in land use in a country; civil protection measures to be implemented will be essential to alert and protect future populations to the occurrence of extraordinary weather events, providing necessary measures in cases such as heatwaves, frosts and floods. In this study ten weather stations with daily records of precipitation and air temperature located in different points of Mexico were selected; monthly behavior patterns of historical rainfall depending on the temperature in a representative year were identified, and genetic programming (GP) was applied to obtain mean temperature-rainfall models. Additionally, climate change models were applied using the system SEDEPECC of the Mexican Institute of Water Technology (IMTA), with horizons from 50 up 10000 years, obtaining forecasts of precipitation and temperature. The GP models were applied with the forecasted data of temperature to approach the rainfall and the annual patterns in some cases were similar to historical values.*

Keywords: *Mean Rainfall, Mean air temperature, Genetic programming (GP) models, climate change*

1. Introduction

The study of the way in which weather variables have gone or will change in the face of greenhouse gas emissions, has been the subject of numerous investigations since the late nineteenth century that have increased since the eighties of the 20st century (De Lima, 2012, Buddaa & Dewalleb, 2001, Boccolari & Malmusi, 2013, Abderrahmane, 2008, Magaña, 2006).
Studies of the analysis of the behavior of precipitation according to climatic variables have been carried out, either correcting their values (Allerup, 2000), or modifying the statistical bias of precipitation and temperature used in hydrological models or in predictions of regional climate change (Piani, 2010, Chistensen, 2008). Homogeneity adjustments have also been made to temperature and precipitation series (Toumenvirta, 2001, Berget, 2005, Brunetti, 2005, Cahalan, 1996). Other studies have analysed the effect of annual total precipitation and average air temperature in annual runoff (Cho, 2011). The effects of the variation in soil cover on annual precipitation and near-surface air temperature have also been studied. (Strack, 2008, De Lima, 2012). Other studies include adjustment to daily or monthly precipitation data or precipitation data given in grids (Yang, 1998, Benning & Yang, 2005, Adam & Lettenmaier, 2003.
Unlike previous studies, where we seek to simulate relatively constant variables, in this paper we try to identify variables that change moderately throughout a fairly wide geospatial territory.
Evolutionary computation, genetic algorithms, genetic programming and other bioinspired algorithms have gained popularity in their use in engineering problems since the last two decades of the 20th century; we can mention the works of Fuentes, 2015. In particular, genetic programming has been used in hydrology and hydraulics to obtain mathematical models in which a dependent variable is related to one or more independent variables. Within the evolutionary computation, genetic algorithms and genetic programming (PG) are tools that help to obtain

parameters of proposed models or to obtain completely new models in their form with which the behavior pattern of a dependent variable can be reproduced in function of n independent variables (Cramer, 1985, Koza, 1989, Goldberg, 1989).
The objective of this study was to obtain, with a genetic programming algorithm, models of the pattern of the behavior of the monthly precipitation based on the temperature of the air that they have observed historically and to use these models to estimate the monthly precipitation with air temperature data, generated under climate change scenarios, in order to identify the agreement between the measured and calculated data. To make the analysis, 10 climatological stations of the Mexican Republic, representative of the different regions of the country, were selected.
The article is organized as follows: first the methodology used is presented from the data analysis, the description of the genetic programming, then the separation of the data is done (horizontal and vertical dissection, based on the differences obtained in those directions with the models that considered all the data) to obtain new models with genetic programming, considering groups of non-consecutive months, the application is subsequently made, the results obtained are highlighted and finally the conclusions derived from the study are reported.

1. Methods

1.1. Data collection and analysis

In Mexico a system of compilation of the normal of the climatological stations is used which is of public domain and is in charge of the National Water Commission (CONAGUA), in this site the following data were extracted from the stations mentioned above:

- Precipitation
- Evaporation
- Maximum air temperature
- Minimum air temperature
- Mean air temperature

But as in any system there is loss of information due to technical failures either as a result of an extreme event, system crash or maintenance of the same station, for which reason it was necessary to resort to adjacent information, that is, to information from attached or nearby stations, which fulfilled the criterion that the distance between one and another did not exceed 20 km apart.
Monthly mean air temperature and precipitation data were selected from 10 weather stations of the CONAGUA, distributed throughout the country (Table 1 and Figure 1).

Table 1: Climatological stations distributed throughout the National Territory

Station	State	Name	Municipality	ID CONAGUA
A	Sinaloa	San Joaquin	Sinaloa	25172
B	Queretaro	Coyotillos	El Marques	22043
C	Chiapas	Cuauhtemoc	Ixtapa	7343
D	Sonora	Colonia Morelos	Agua Prieta	26022
E	Yucatan	Santa Elena	Santa Elena	31027
F	Veracruz	Chicontepec	Chicontepec	30041
G	Michoacan	Acahuato	Apatzingan	16228
H	Guerrero	Acapulco	Acapulco	12142
I	Baja California Sur	Ojo de Agua	Comondu	3039
J	Coahuila	Ejido Primero de Mayo	Escobedo	5147

Fig. 1. Map location of climatological stations

1.2. Genetic programming (GP)

Genetic programming (GP) (Koza, 1992) takes place in a few years later the genetic algorithms (Goldberg, 1989), in order to build computer programs and mathematical models using evolutionary random algorithms used as optimization methods.

The genetic programming algorithm includes the establishment of the independent variables and the dependent variable in the problem, operators and constant vector to be considered for the construction of the models to be tested must also be defined. It should provide a probability of exchange or cross (crossing) of the best individuals (set of selected operations) and a probability of mutation must be given. A number of generations (iterations) is proposed to finish the optimization process. In this study objective function consisted in minimizing the mean square error between the measured and the calculated rainfall data with the models tested by the GP algorithm.

The GP algorithm starts with the random generation of an initial population of n individuals (each individual corresponds to a mathematical model consisting of different operators, variables and constants), individuals are then evaluated in the objective function and the best ones are selected (selection can be performed by obtaining a relative frequency of the result obtained by each individual in the objective function divided by the average value given by all tested individuals), individuals with higher relative frequency can be used more than once to be exchanged or crossover, and mutation may also create new individuals and the individuals with lower performance are eliminated and no longer enter the exchange process and / or mutation; so that the new population is again size n. The new individuals are again tested on their performance, selected and the best ones creates new individuals who pass to the next generation, this process is repeated until the number of generations or iterations is reached and the best individual in the last generation will be the one with higher performance and represents the optimal mathematical model found; in Figure 2 there is a flow chart of GP Algorithm.

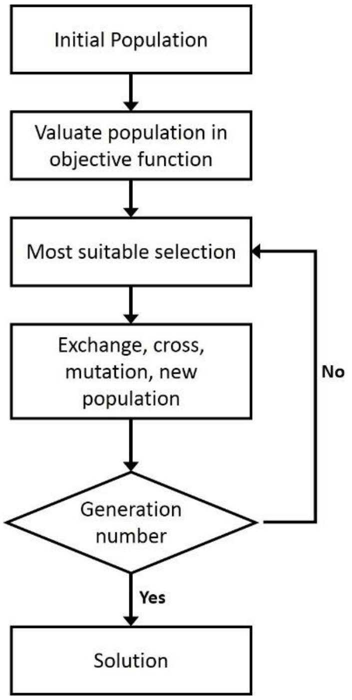


Fig. 2. GP Algorithm

In this study the set of arithmetic operators TS = [+,-,*] was considered, a vector of constants obtained randomly, there were considered the independent variable air temperature T and the rainfall hp as dependent variable. Populations of 200 individuals (models) of 25 nodes (consisting of operators, variables and constants), a crosses a probability of 0.9 and mutation probability of 0.05 were considered; finally, 5,000 generations to complete the process were considered.
The objective function consisted of minimizing the mean square error between the measured and calculated data with the test model.

$$Z = \min \frac{1}{n} \sum_{i=0}^{n} \left(Hp(T) - \widehat{Hp(\overline{T})} \right)^2 \tag{1}$$

Where *Hp(T)* is the historical monthly rainfall intensity in mm/day, *Hp(T̅)* is the calculated rainfall intensity in mm/day, as a function of the monthly average temperature *T in C°*

1.3. Domain Splitting

For each station, a monthly precipitation model was obtained with genetic programming based on the temperature, considering all the months of the representative year (12 data); a graphic comparison was made between the measured and calculated precipitation data and it was decided to divide the domain of the problem considering the months of registration separately; genetic programming was re-applied to obtain new functions; that is, on this occasion 12 different equations were obtained, taking as reference the time of year.

1.4. SEDEPECC Platform

The SEDEPECC Platform of IMTA uses different scenarios of climate change and its records were taken as a basis in this work; but such platform does not provide a suitable accuracy for each climatological station of the CONAGUA database, the platform only estimates site data with an approximation of 0.5 °, since the coordinates are limited to a type of scenario A1B (High Emissions), for a period from January 2010 to January 2060, with data corresponding to the normal or means for each year, the temperature and rainfall intensity data were collected. (Figure 1 shows the location of the points near the stations of the CONAGUA that were considered for the data download of the SEDEPECC platform). Figures 3 to 8 illustrate the steps taken for the compilation of climate change data.

Fig. 3. The type of Climate Change Scenario is selected, in this case the A1B

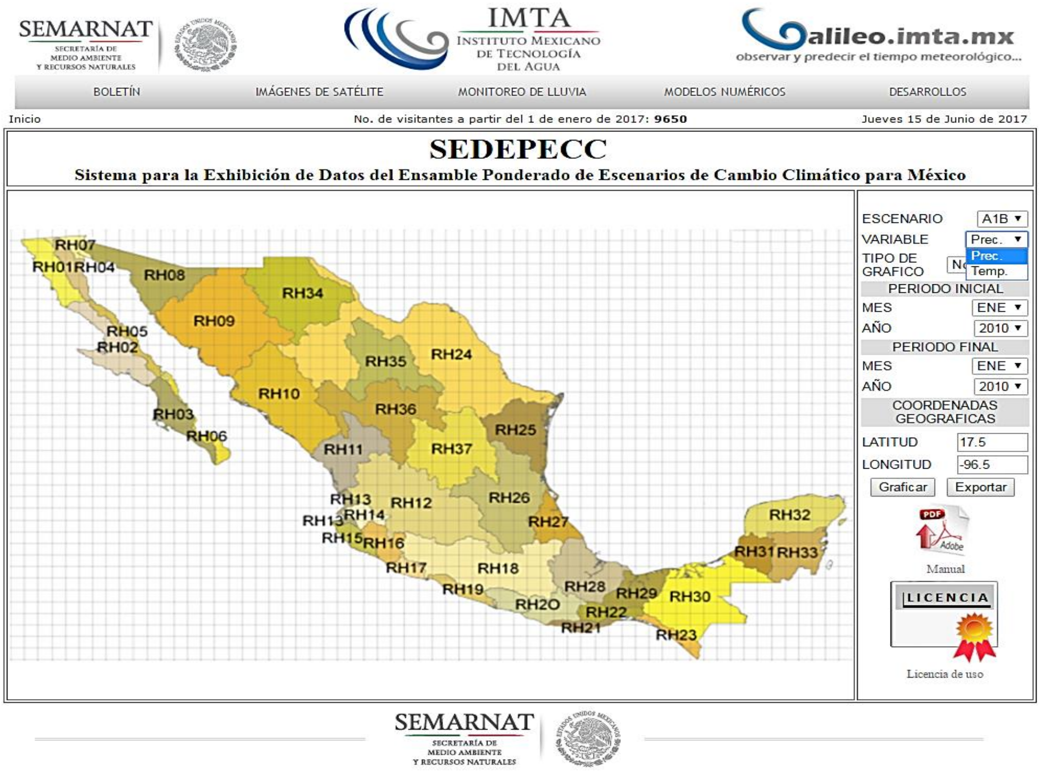


Figure 4: The variable (Temperature or Precipitation) is defined.

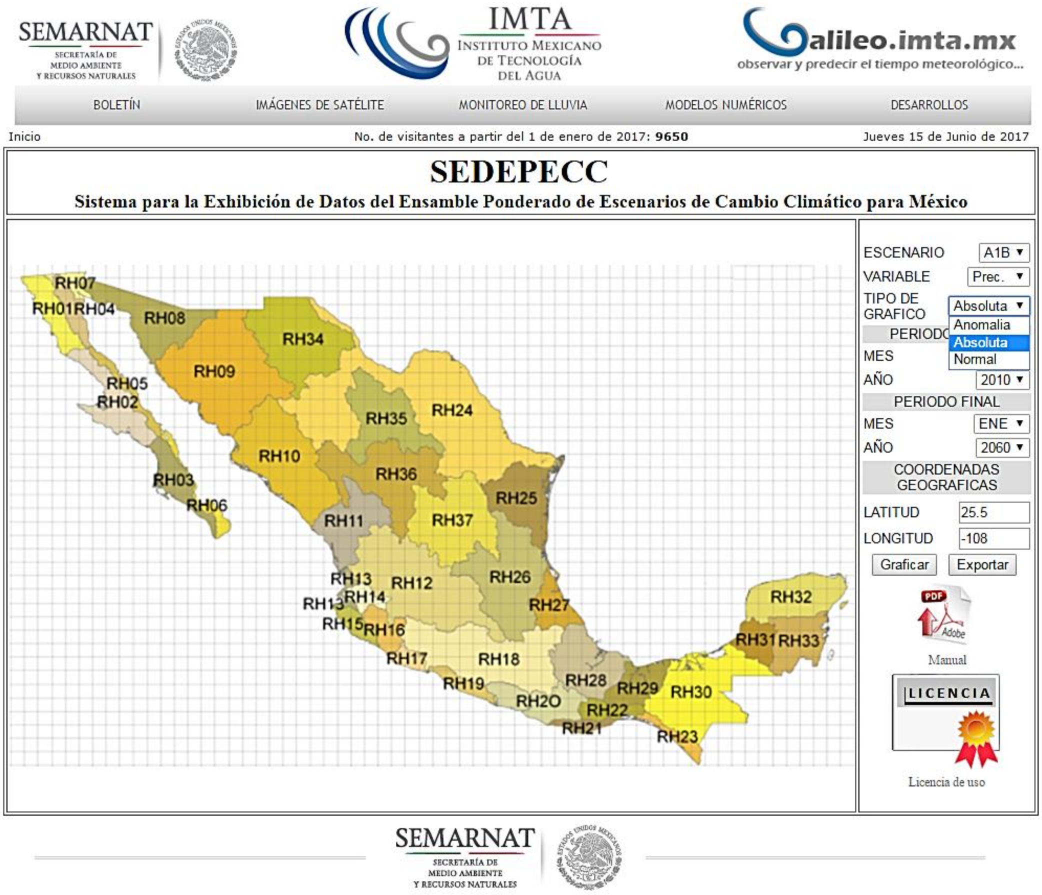


Fig. 5. To obtain data for each month, an ABSOLUTE graph is specified

Fig. 6. The period to be analyzed is limited

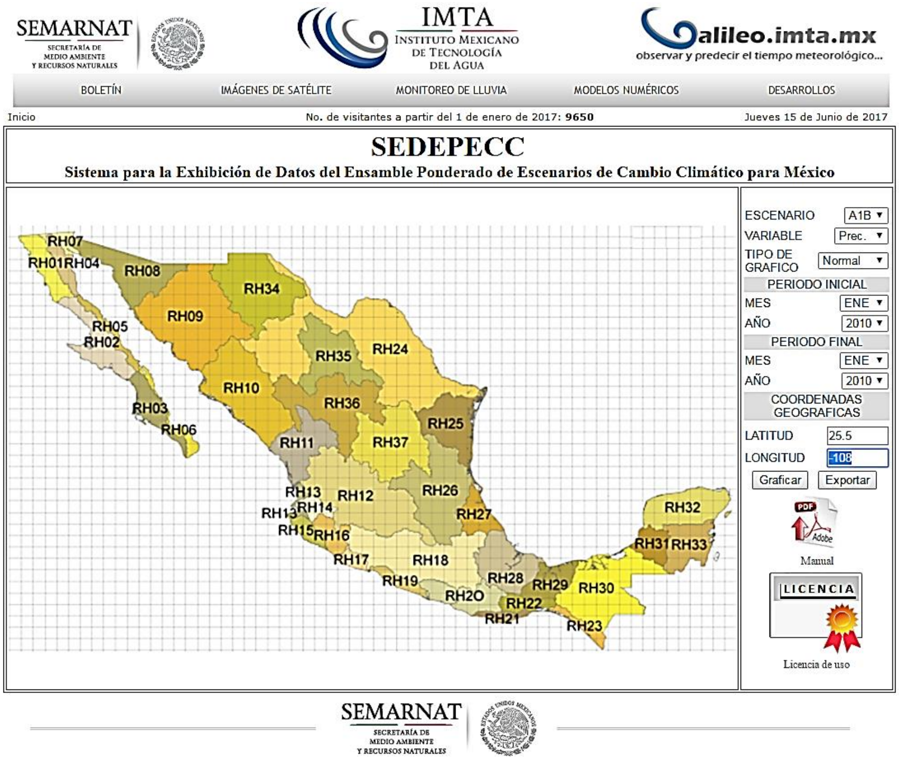
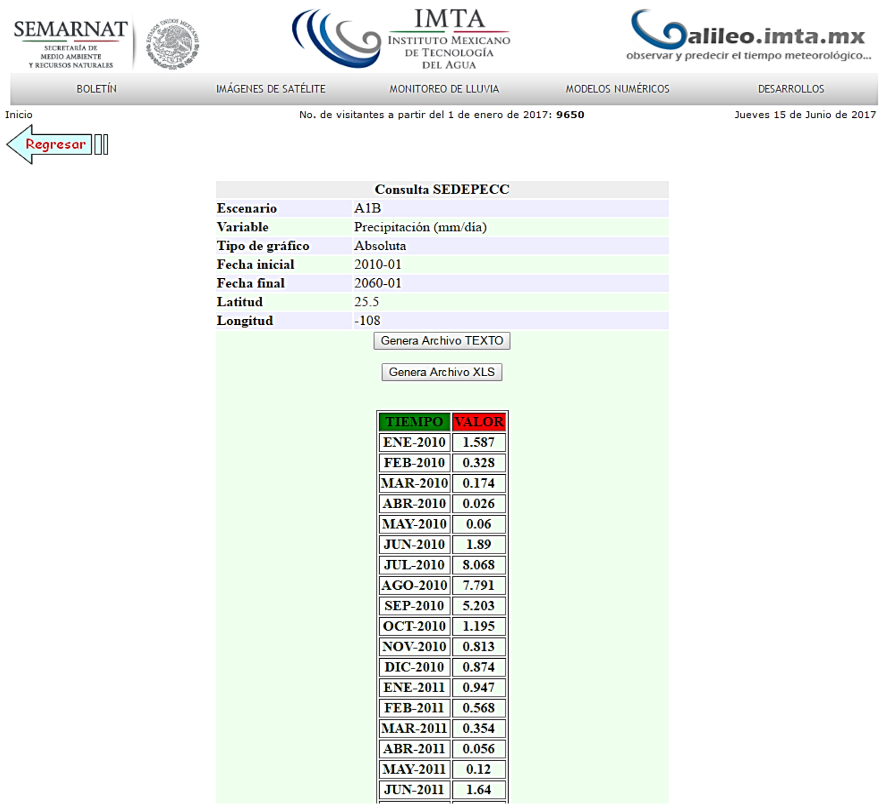


Fig. 7. The coordinates of the site under study are loaded, bearing in mind that the platform has an accuracy of 0.5°



Consulta SEDEPECC	
Escenario	A1B
Variable	Precipitación (mm/día)
Tipo de gráfico	Absoluta
Fecha inicial	2010-01
Fecha final	2060-01
Latitud	25.5
Longitud	-108

TIEMPO	VALOR
ENE-2010	1.587
FEB-2010	0.328
MAR-2010	0.174
ABR-2010	0.026
MAY-2010	0.06
JUN-2010	1.89
JUL-2010	8.068
AGO-2010	7.791
SEP-2010	5.203
OCT-2010	1.195
NOV-2010	0.813
DIC-2010	0.874
ENE-2011	0.947
FEB-2011	0.568
MAR-2011	0.354
ABR-2011	0.056
MAY-2011	0.12
JUN-2011	1.64

Fig. 8. The option EXPORT is chosen and later it can be used in the desired format

1.5. Application of PG models to series of climate change scenarios

In order to simulate the behavior obtained with the representative year and with the horizontal and vertical dissections, the models were fed with air temperature records extracted from climate change scenarios from the SEDEPECC platform to obtain the indispensable equation to calculate the precipitation of the site study. Initially records with a length of 50 years were used, later periods between January 2010 and January 2045 were adopted (that is 35 years to obtain the model), with the intention of testing the equations in the subsequent 15 years, seeking to represent the behavior of the simulations represented in the SEDEPECC.

2. Results

Notably the values calculated with the PG follow the same behavioral trend as the data disseminated by the SEDEPECC, this is of note, since, when trying to reproduce the patterns in the following 15 years of study with the formulas obtained with the initial 35 years, the behavior of the figures coincides and, in addition, the divergence is lower between those calculated and those taken as a basis. The scope of these results is visible in table 2 and from figure 9 to 11.

Table 2: Precipitation Intensity Equations (mm/day), obtained with PG according to the month of adjustment

San Joaquin Station, Sinaloa, ID: 25172	
January Equation	$Hp = 0.94$
February Equation	$Hp = -0.004T^2-0.01T+2.03$
March Equation	$Hp = 0.801-0.0000029T^4$
April Equation	$Hp = 0.0802$
Mayo equation	$Hp = 0.0005T^2+0.00003T-0.223$
June equation	$Hp = 4.789-0.097T$
July equation	$Hp = 8.321$
August equation	$Hp = -0.0006T^3+0.0084T^2+0.499T-0.089$
September equation	$Hp = 0.0076T^2-0.0329T$
October equation	$Hp = 4.667-0.11T$
November equation	$Hp = 0.635$
December equation	$Hp = -0.0000017T^4+0.00019T^3+0.00011T^2+0.000016T$

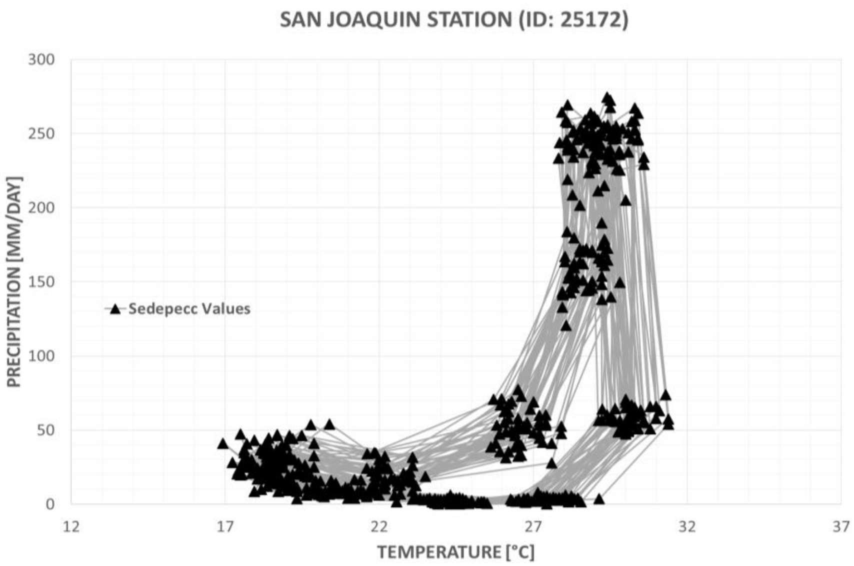


Fig. 9. Values of the SEDEPECC platform, corresponding to an A1B scenario, with a period between January 2010 and January 2045. Site near San Joaquin Station

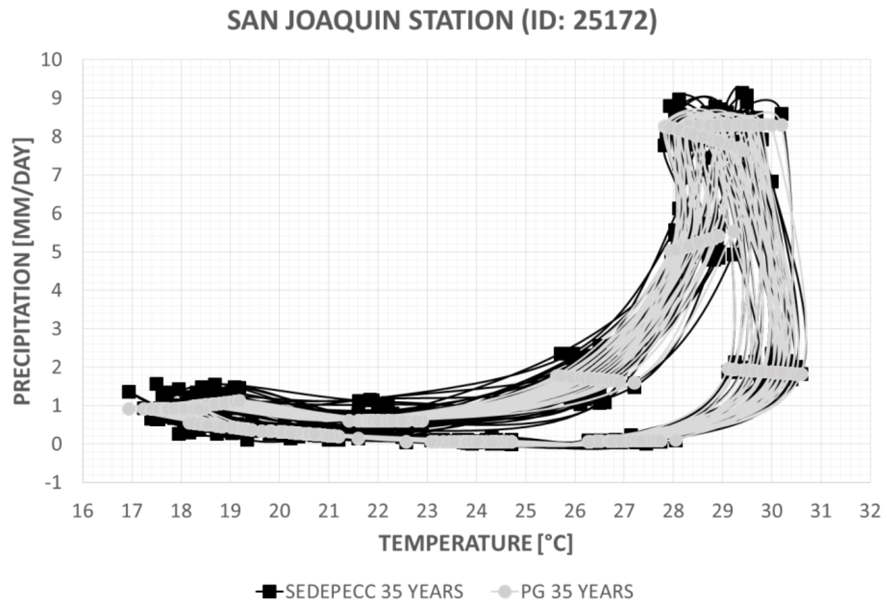


Fig. 10. Precipitation against Temperature, PG and SEDEPECC first 35 years

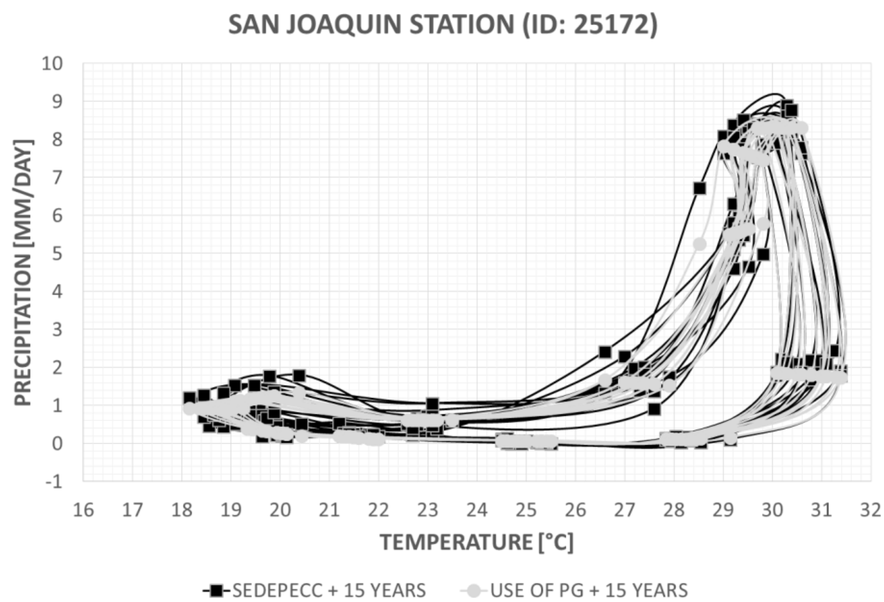


Fig. 11. PG model obtained with firs 35 years used to the subsequent 15 years

Figure 12 shows the efficiency of the method since it is possible to reproduce the annual behavior pattern of precipitation from the average air temperature data. Below are the graphs that are obtained by applying the same equations to a much longer time span, for this case from February 2045 to December 2098.

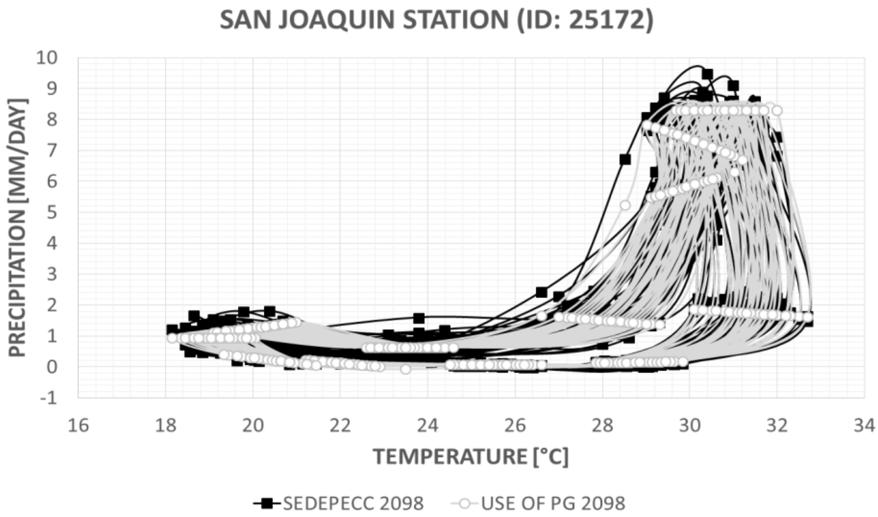


Fig. 12. PG with 35 initial years used for a period of time longer than 53 years on the chart of the SEDEPECC records for the same subsequent period

The parameters obtained from this process are listed below (Table 3), show that Genetic Programming can be used to calculate long and short term behavior based on an initial period of 35 years.

Table 3: Parameters calculated for different subsequent periods

San Joaquin Station, Sinaloa, ID: 25172	
Mean Square Error 35 initial years	*0.08*
Mean Square Error Feb 2045 to Jan 2060 PG	*0.09*
Mean Square Error Feb 2045 to Dec 2098 PG	*0.15*
Variation 35 initial years	*8.51*
Variation 35 years PG	*0.08*
R^2 35 years PG	*0.99*
Variation Feb 2045 to Jan 2060	*8.68*
Variation Feb 2045 to Jan 2060 PG	*0.11*
R^2 Feb 2045 to Jan 2060 PG	*0.99*
Variation Feb 2045 to Dec 2098	*7.92*
Variation Feb 2045 to Dec 2098 PG	*0.21*
R^2 Feb 2045 to Dec 2098 PG	*0.97*

3. Discussion

There is still a long way to go when it comes to predicting climatological variables, but what is detailed in this work will be used to generate opinions and highlight the importance of being prepared as a society in the face of extreme events. the results shown in graphs and make an analysis in the peaks in both low and high temperatures and how these can give indications of the behavior of the climate in specific regions.

4. Conclusion

In this work, models were obtained to reproduce the patterns of precipitation behavior based on their average temperature in different sites of Mexico, with unique physiographic and hydrographic characteristics, providing a tool for the prediction of meteorological phenomena of certain regions, before of short and long-term climate change.

In the modeling of data based on the same figures of SEDEPECC, and used in later periods in the short and long term, excellent adjustments were also found, such as the San Joaquín Station, Sinaloa, Code 25172, since the parameter of R2, was the highest in its three periods of analysis.

As mentioned previously, this research has covered 10 stations in the Mexican national territory, so it is important to capture the most outstanding results in a general manner, in figure 13 and 14 a global summary of this study is shown.

Month	Station				
	San Joaquin	Coyotillos	Cuauhtemoc	Colonia Morelos	Santa Elena
January	0.94	0.706-0.02998T	3.840-0.104T	-0.025T+0.62	0.8228
February	-0.004T^2-0.01T+2.03	0.002T^2-0.085T+1.16	3.24-0.075T	-0.0044T^2-0.0022T+0.81	0.7659
March	0.801-0.0000029T^4	1.197	2.71-0.0578T	-0.00016T^2+0.986	0.9052
April	0.0802	-0.003T^2-0.0006T+1.8	4.858-0.129T	0.0396	1.0894
May	0.0005T^2+0.00003T-0.223	7.3-0.26T	5.207-0.067T	-0.0009T^2+0.0023T	2.82-0.006T
June	4.789-0.097T	-0.03T^2+0.82T-0.053	12.378-0.217T	0.995-0.0239T	-0.02T^2+0.77T-0.52
July	8.321	-0.039(T-24.04)(T-1.99)	-0.029T^2+0.917T+1.09	0.436T-0.0125T^2	12.32-0.27T
August	0.0084T^2+0.499T-0.089	6.155-0.155T	-0.03T^2+1.05T-0.021	0.0599T+0.785	4.32
September	0.0076T^2-0.0329T	7.05-0.19T	9.025	5.892-0.193T	23.49-0.61T
October	4.667-0.11T	0.074T+0.159	0.115T+3.53	0.712	5.34-0.053T
November	0.635	0.00002T^3-0.002T^2+0.798	-0.0099T^2+0.358T+0.087	0.41	1.446
December	0.00011T^2+0.000016T	0.8229-0.0449T	-0.01T^2+0.32T-0.214	0.612	2.499-0.044T

Month	Station				
	Chicontepec de Tejeda	Acahuato	Acapulco de Juarez	Ojo de Agua	Ejido Primero de Mayo
January	-0.003T^2+0.065T+1.173	-0.00035T^2+1.28	1.008-0.038T	0.0096T+0.159	2.124-0.13T
February	1.495	1.09-0.002T^2	1.05-0.046T	0.856-0.0459T	-0.00003T^2+1.31
March	1.125	2.72-0.12T	1.43-0.06T	0.0516	0.223
April	5.108-0.118T	-0.001T^2	0.994-0.001T^2	0.267-0.013T	0.762
May	-0.007T^2+0.255T+0.79	0.92	1.32	0.0175	3.765-0.075T
June	-0.0169T^2+0.665T+2.168	-0.036T^2+1.08T+1.314	-0.029T^2+1.012T-0.69	0.00001T^3	5.78-0.14T
July	11.21-0.18T	-0.039T^2+1.235T+0.73	7.197	0.002T^2-0.03T-0.0123	8.11-0.22T
August	5.25	9.71-0.05T	-0.017T^2+0.64T+1.46	1.57	1.35
September	-0.02T^2+0.9997T+0.799	0.26T+3.56	-0.029T^2+1.12T-0.0297	1.33	-0.011T^2+0.45T-1.12
October	0.224T+0.04	0.37T-4.31	-0.0049T^2	-0.008T^2+0.129T+0.667	1.0447
November	8.41-0.25T	0.78	0.043T	0.746-0.0329T	-0.005T^2+0.065T+1.219
December	0.12T-0.73	2.22-0.102T	0.0014T+0.031	0.3919	0.2576

Fig. 13. Equations obtained monthly

Parameter	Statiion									
	San Joaquin	Coyotillos	Cuauhtemoc	Colonia Morelos	Santa Elena	Chicontepec de Tejeda	Acahuato	Acapulco de Juarez	Ojo de Agua	Ejido Primero de Mayo
Mean Square Error 35 initial years	0.08	0.09	0.17	0.04	0.07	0.15	0.12	0.13	0.02	0.07
Mean Square Error Feb 2045 to Jan 2060 PG	0.09	0.1	0.17	0.04	0.08	0.16	0.13	0.13	0.02	0.07
Mean Square Error Feb 2045 to Dec 2098 PG	0.15	0.17	0.2	0.06	0.1	0.19	0.17	0.18	0.03	0.09
Variation 35 initial years	8.51	1.98	6.71	0.73	3.3	11.05	14.26	12.64	0.29	0.51
Variation 35 years PG	0.08	0.09	0.17	0.04	0.07	0.15	0.12	0.13	0.02	0.07
R^2 35 years PG	0.99	0.96	0.97	0.95	0.98	0.99	0.99	0.99	0.93	0.87
Variation Feb 2045 to Jan 2060	8.68	1.99	6.52	0.73	3.13	11.06	14.08	11.99	0.3	0.5
Variation Feb 2045 to Jan 2060 PG	0.11	0.13	0.16	0.05	0.11	0.18	0.14	0.12	0.03	0.08
R^2 Feb 2045 to Jan 2060 PG	0.99	0.94	0.98	0.94	0.96	0.98	0.99	0.99	0.9	0.84
Variation Feb 2045 to Dec 2098	7.92	1.91	5.67	0.8	2.94	10.98	14.14	11.88	0.24	0.5
Variation Feb 2045 to Dec 2098 PG	0.21	0.23	0.24	0.08	0.12	0.23	0.21	0.25	0.04	0.11
R^2 Feb 2045 to Dec 2098 PG	0.97	0.88	0.96	0.9	0.96	0.98	0.99	0.98	0.84	0.78

Fig. 14. Parameters obtained monthly.

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