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# Time Series Forecasting of Rainfall in Alicante Spain

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## ABSTRACT

***In this study, the preoccupation was to determine the most effective analysis tools for precipitation forecasting using the ARIMA model and Multiple Linear Regression. Therefore, as displayed in figures 1.5 to 1.9, data depict the multiple linear regression model as the most effective in handling rainfall/precipitation modeling compared to the ARIMA model. The results generated in multiple linear regression present a 95% confidence level as displayed in the set of data within the probability plot. The results further depict that the relationship between variables involves in the ARIMA is correlative given the 5% value of the ACF. Hence, ARIMA and MLR analysis were applied to data sets, thus developing the weights and regression for the coefficient. In doing so, the performance of models is checked on the bases of the resulting R-Squared values. Judging from all indications Multilinear Regression model has proven more preferable over the ARIMA model in terms of performance given its R-Squared value that stands at 92.83.***

## 1. INTRODUCTION

Precipitation plays a fundamental role in the drainage of hydrographic basins, particularly those that rely on precipitation for the continued existence of rivers, which are considered intermittent currents. These types of occasionally dry streams are large-scale phenomena (1-2) and could potentially increase under climate change conditions. Therefore, the intensity and magnitude of precipitation events are an important part of hydrological models for simulating and predicting flooding in these catchments ( 6 ), and knowing the thresholds required to generate new flew helps help to address natural hazards from a hydrological modeling perspective (9 ). Ephemeral streams are drainage networks that remain completely dry for a variable period of the year and, due to rainfall events of a certain magnitude, can discharge relatively high runoffs that can last for some time. The western area of the

Mediterranean Sea is particularly vulnerable to basins with these types of currents, both spatially and temporally, due to the high irregularity of rainfall (11). In ephemeral flows, this irregularity becomes a major uncertainty in power generation, affecting not only the stream but other parts of the system as well. For example, the volatility of the rivers alters the real-world ecological functioning of the basin by varying magnitudes and naturally affects the agricultural systems that cover the lowlands, which generally require infrastructure to recover.

## 1.1 CLIMATE CHANGE AND WATER RESOURCES

Climate change is one of society's alarming problems in the 21st century. Despite the uncertainty about the behavior of rainfall due to climate change, what is clear is that average rainfall has been reduced in the inland areas and headwaters of Spain's river basins. By the IPCC Sixth report, as published in 2021, the Mediterranean region is pruned to climate change on a global scale. And Spain is no exception. Consequently, Spain is certainly stricken by varieties of climate effects ranging from meteorological conditions, like flooding, drought heat, cold wave, sea storms, forest fires, etc. Additionally, Spain is meteorologically known for its broad scope of climate variation that supports its various geographical features. More besides, Spanish humidity is highly susceptible to a wide range of rainfall thus posing severe bottle nick to Alicante and other cities within the north and central peninsula region. During few decades glob population demand for water resources has exponentially severed on water resources supply. As result, 20% of the global population demands groundwater for daily water supply (10). Interestingly the day-to-day economic activities are tied to the ground. Consequently, arid and semiarid-pruned regions heavily relied on groundwater as the only semiarid-pruned source (8). Corroborativelly, Alicante's economy entirely feeds on groundwater. Succinctly, Alicante hydrological linings are noted for its carbon, Cretaceous, limestone, and dolomites pruned aquifers. In alignment with the latter, weathering erosion of rocks within the aquifers has over time rendered water quality very poor (2).

## 1.2 WATER RESOURCES IN ALICANTE

The province of Alicante in southern Spain is one of those regions where groundwater has been intensively exploited for more than sixty years. This has been accompanied by a significant change in the landscape due to the increase in cultivated land. At the same time, tourism has also developed in the province of Alicante. Alicante is a region with scarce water resources, but its location in the semi-arid southeast of the peninsula, and the lack of significant permanent rivers mean that water needs cannot be met with surface water, so water supply requires the use of groundwater. Over the years, the development of society has increased pressure on natural resources, resulting in numerous problems of overuse of many underground water reservoirs, with effects such as a significant decline in piezometric levels, drying up of springs, impacts on surface waters associated with groundwater, salinization of aquifers, and impacts on aquatic ecosystems (1-3). Currently, 11.4% of the supply comes from desalination and 11.5% from reuse/treatment.

The hydrographic basins of Alicante Alta are immersed in a semi-arid climate that characterizes the area of the southeastern peninsula. Annual rainfall with a pronounced equinoctial regime (maximum in March-April and September-October) rarely exceeds, 300 linear metric units (1-4) and is very variable depending on the season and also the year. Changes in precipitation regime (and possible associated flood events) may affect the river's supply of sediments and alternative matter to the coastal zone. Rather, we expect that this will also apply to landfills of waste materials (livestock and agriculture, industry or urban), which are somewhat more conditioned by the nature and intensity of current and future economic activities and the corresponding activities. Preventive or corrective action, rather than changes in precipitation patterns.

## 1.3 EMPIRICAL MODELS

Empirical modeling is a generic term for activities in which models are created through observation and experiment. Empirical modeling (with initial capital letters and often abbreviated as EM) refers to a specific variant of empirical modeling in which models are created according to specific principles. Undoubtedly, computer technologies have fundamentally changed the full exploitation of the principles of empirical modeling.

Empirical modeling strives to establish correspondence between the model and its referent in such a way that its derivation can be traced back to connections given in experience. Making connections in experience is an essentially individual human activity that requires skill and is highly context-dependent (Wikipedia). Henceforth, in order to effectively derive an informed on the suitability of specific modeling tools in predicting rainfall, the study incorporated both ARIMA and Multi Linear Regression in predicting rainfall in Alicante Spain.

### 1.4 AIM OF THE STUDY

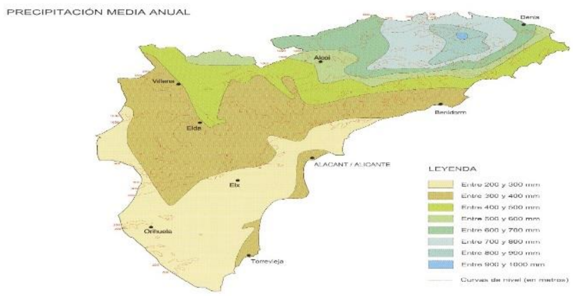
This paper aims to identify the best model for the prediction of annual precipitation in Alicante, a city located in Spain. Additionally, the two models are evaluated using their R-squared values, and confidence levels. Moreover, the study seeks to provide the seasonality trend of rainfall in the area of consideration, concerning climate change and its impacts. Furthermore, the research engenders the expansion of the body of knowledge, through the discovery of additional study focus. Having said so, the researcher used Minitab and Excel to model the annual rainfall data of Alicante. Finally, this study intended to further probe into understanding the actual accuracy associated with predicting rainfall through the utilization of the following functions, Multiple linear regression (MLR) and autoregressive integrated moving average ARIMA for short. The primary focus of the researcher during the execution of this task was to properly define the characteristics of the variable given the usage of each statistical function. By doing so, the researcher detailed all of the outcomes of the analysis.

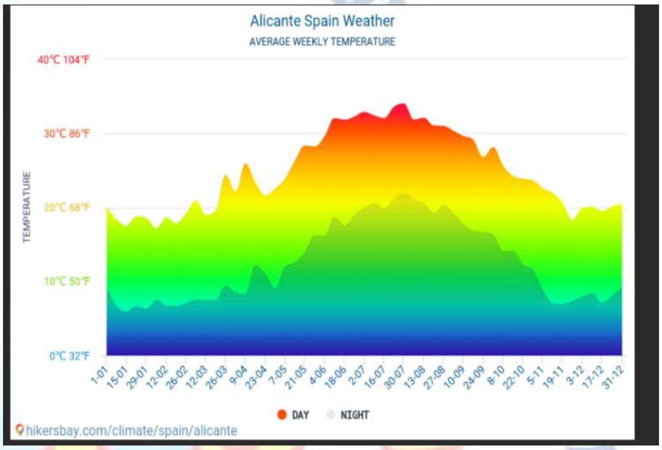
## 2. MATERIALS & METHODS

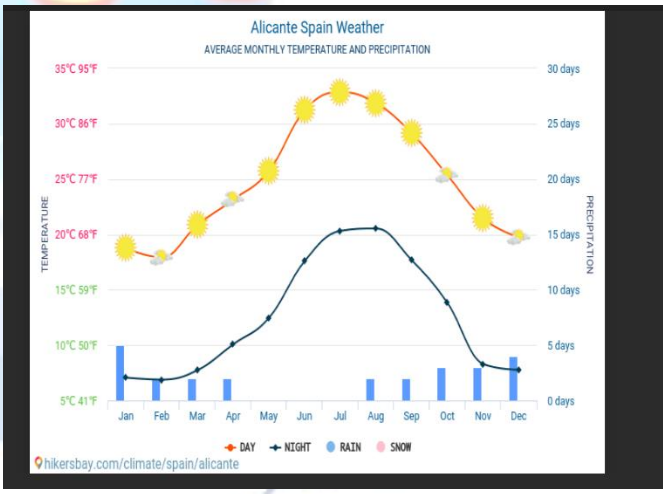
### 2.1 *STUDY AREA*

The study focuses exclusively on Alicante a port City located in Spain. Geographically, Alicante is located on the eastern Mediterranean coast of Spain, thus forming borders with lots of inland mountains. Based on its location it has a fair share of the typical Mediterranean climate, hot summers, mild winters, and a little rainfall. Interestingly, it also has a yearly average temperature of 18$^{0}$C (65$^{0}$F). Additionally, it is spatially located on the globe by the following spatial reference 38°20'42.6'' N 0°28.889' W. Moreover, the study area is noted for its attraction thus below the figure is an average precipitation map of Alicante.

### 2.2 *MAP*



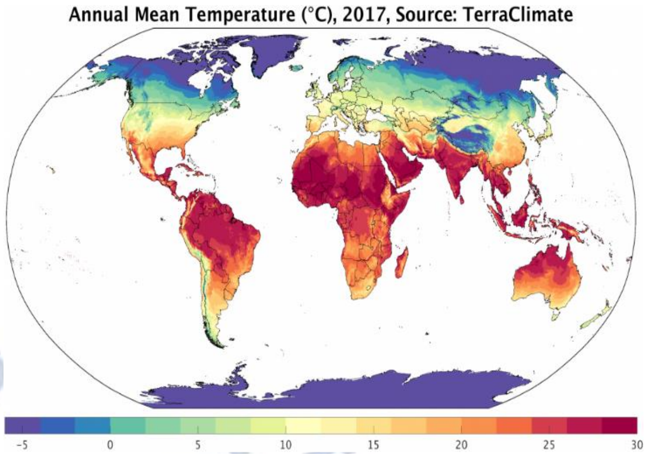




### 2.3 *DATA SET*

#### *SATELLITE DATA*

Satellite data is the process of remote sensing that allows a researcher to acquire data from unreachable targets. TerraClimate (4) is a dataset of monthly climate and climatic water balance for global terrestrial surfaces from 1958-2020. These data provide an invaluable contribution to global-scale ecological and hydrological studies that require high spatial resolution and temporally varying data. The temporal resolution of the data is monthly and the spatial resolution is 4 km (1/24th degree). TerraClimate is freely available at GEE. Moreover, primary climate variables are fashioned after the following parameters, maximum temperature, minimum temperature, vapor pressure, precipitation accumulation, downward shortwave surface radiation, and wind speed. However, variables derived from the primary variables are reference evapotranspiration (ASCE Penman-Monteith), Runoff, actual evapotranspiration, climatic water deficit, soil moisture, and snow water equivalent, Palmer drought severity index (PDSI), vapor pressure deficit. TerraClimate uses climatological normal values with a high spatial resolution (30-year average for one season) from the WorldClim dataset (worldclim.org) and time-varying (i.e., monthly) data with coarser spatial resolution (i.e., monthly) data from the gridded time series of the Climatic Research Unit (CRU Ts4.0) and the Japanese 55-year reanalysis (JRA55). World Climate (3) interpolates weather station data with satellite-derived (MODIS) covariates of maximum and minimum land surface temperature and cloud cover. CRU grids an extensive network of weather station observations 14. JRA55 uses satellite-derived data (various sensors), with ERA -40 as the main data source for the interpolations. Theoretically, the technique applies interpolated time-varying anomalies from CRU Ts4.0/JRA55 to WorldClim's high spatial resolution climatology to produce a high spatial resolution dataset covering a larger temporal domain. Temporal information is extracted from CRU Ts4.0 for most global land areas for temperature, precipitation, and vapor pressure. JRA55 data are used for areas for which CRU had no climate stations (Antarctica and parts of Africa and South America.). In addition, TerraClimate produces simplified monthly surface water balance datasets using a water balance model that incorporates reference evaporation, precipitation, temperature, and interpolated plant-extractable soil water capacity. The limitations of TerraClimate are mainly the scale (spatial and temporal) of the output datasets and the limited validation in data-poor regions. It should not be used directly for independent assessments of trends (4).




### 3 *IMPORTANCE OF SATELLITE DATA*

Satellite data are an essential resource for climate monitoring, including their use in reanalysis. Data recovery is an important activity for satellite data owing to the rationale that, it has the potential to extend time series. Interestingly, the value of historical data has increased dramatically in recent decades, from providing imagery to quantitative data for assimilation and retrieval. Modern satellite data such as ASCAT has value beyond its original purpose. In a quest to effectively provide resourceful information on climate science and services to society, the extensive utilization of satellite data is unavoidable. Satellite ultimately provides absolute liberty in terms of global climate data acquisition upon a click. Moreover, it proffers real-time high spatial coverage coupled with some temporal coverage. Interestingly satellite temporal coverage derives climate scale data for the period of 40 years. And as such, data collected from targets are difficult or impossible to access via ground measurements. Advantageously, satellite data contain high accuracy, thus providing important data for modeling weather and climate variables. finally, satellite data in its nature are very organized and globally collaborative (12).

### 4 **Advantages and Disadvantages of Terraclimate**

Combines spatially finely resolved climatology with temporal information for the period from 1958 to the present. In addition to standard monthly climate summaries, TerraClimate provides variables of more immediate use to ecology and hydrology for surface hydroclimate, including runoff, actual evapotranspiration, soil moisture, and climatic water deficit, which are the data available for download or online visualization. Climate-based interpolation interpolates anomalies from the coarser-resolution output product (e.g., CRU Ts at 0.5-degree resolution) into climatology at higher spatial resolution. Therefore, sharp gradients in climate anomalies in montane or coastal environments are not detected because TerraClimate does not capture the temporal variability of climate measurements at finer scales than the parent product. TerraClimate should not be considered an independent estimate of trends in variables such as temperature. Basic uncertainties in the core data sets used, including negative precipitation biases in the mountains of the western U.S., inherited from World Climate, or inhomogeneities CRU TS or reanalysis, are included in TerraClimate. A very simple water budget model is also used (4).

## 3.MODEL

### *3.1 MULTIPLE LINEAR REGRESSION*

According to Investopedia multiple linear regression is a statistical process that utilizes many explanatory variables to predict the outcome indicators of the presence of another variable. The driven intent of employing the approach is to model the linear relationship between independent and dependent variables. By extension, MLR is certainly associated with the least-squares (OLS) regression, in that it entails multiple explanatory variables. Interestingly, this approach is widely used in making weather forecasting, and econometric and financial inferences. By operation the below formula is considered when performing multiple linear regression analysis:

$$yi = \beta 0 + \beta 1\, xi1 + \beta 2\, Xi2 + \cdots + \beta p\, Xip + E$$

Where, for i=n observations:

Yi=dependent variable

Xi=explanatory variables

$\beta_0$= y-intercept

βp= slope coefficient for each explanatory variable

E= the model's error terms ( also known as residual)

### *3.2 INTEGRATED MOVING AVERAGE (ARIMA)*

Box and Jenkins (1970) fostered this anticipating procedure which is still extremely famous among hydrologists. The autoregressive coordinated moving typical ARIMA (p,d,q) model of the time series {r1, r2,… ..} is characterized as

$$\varphi(B)\, \Delta^d r_t = \theta(B)\, e_t \quad \ldots\ldots(1)$$

Where $r_t$ and $e_t$ separately address mean yearly precipitation time series and irregular mistake terms now and again. B is the regressive shift administrator characterized by $Br_y = r_y\text{-}1$ and connected with $\Delta$ by $\Delta$ = 1-B; d is the request for distinction. The $\phi$ (B) and $\theta$ (B) of requests p and q are characterized as

$$\Phi (B)=1- \phi_1 B- \phi_2 B^2-\ldots\ldots \phi_p B^p \ldots\ldots(2)$$

$$\theta ( B)=1- \theta_1 B^2- \theta_2 B^2-\ldots\ldots \theta q B^q\ldots\ldots(3)$$

where, $\phi_1$, $\phi_2$, … … $\phi_p$ are the autoregressive coefficients and $\theta_1$, $\theta_2$, … ..$\theta_2$ are the moving midpoints coefficients, for additional subtleties, see (Box and Jenkins, 1976). In this ARIMA (p, d, q) display, the initial step is to decide if the time series is fixed or non-fixed. If it is non-fixed, it is changed into a fixed time series by applying a reasonable level of differencing by choosing the legitimate worth of d. The fitting upsides of p and q are picked by analyzing the autocorrelation work (ACF) and halfway autocorrelation work (PACF) of the time series.

Regarding Econometrics and statistics, the autoregressive integrated moving average is an asset in predicting trends coupled with time series analysis. These tools help developers, engineers, business managers, and environmentalists to make informed decisions in terms of predicting the trend across interconnected and different variables. This model is applied when data display empirical evidence of non-stationarity, thus subsequently canceling seasonal deference in the data set. The ARIMA model's purpose for measurable examinations is blended with precisely gathered authentic information and focuses to anticipate future patterns and business needs. The ARIMA model is commonly meant for the boundaries (p, d, q), which can allocate various qualities to alter the model and apply it in various ways. A portion of the constraints of the model is its reliance on information assortment and the manual experimentation process expected to decide boundary esteems that fit best. To effectively apply ARIMA as a professional within the area of metrology consideration of the below formula is key to results-driven and decision -focus trend prediction.

**Single-moving average formulas**

t − p + 1

(Fit)$F = \frac{1}{p}\sum_{k=t} Y_t$

( Forecast for period m)$F_{t+m} = F_t$

whereas parameters are:

P- order of moving average

The predictor uses the following equation for the moving average methods:

(Level) $L_t = 2 * M_t - M'_t$

(Trend)$T_t = \frac{2}{p-2}\ (M_t - M'_t)$

(Fit )$F = L_{t-1} + T_{t-1}$

Forecasting period for (m)$F_{t+m} = L_t + m*T_t$

Whereas the parameters are:

P – Order of the moving average

$M_t$---First order moving average for period t

$M'_t$---- Second order moving average for period t

## 4. MODEL ACCURACY

The R-squared (R2) is a measure of the goodness of the regression line to the measured values and is also called the coefficient of determination. This tool can be very useful in assessing the quality of the estimator in linear regression. Unfortunately, as mentioned at LS, it can also be said that the coefficient of determination is sensitive to outliers and can severely affect the quality of the model. The coefficient of determination is reported with values ranging from zero to one, where a poorly fitting line is represented by a value close to 0, while values close to 1 represent the best fit. We used this tool as a measure of the accuracy of fit in the presence of outliers and how outliers affect the regression analysis. The R2 can be represented in the following:

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$$

$$= 1\ \frac{\sum_{i=1}^{n} (yi - \hat{y})^2}{\sum_{i=1}^{n} (yi - \hat{y})^2}$$

Where ESS, T SS, and RSS are the sum of the squares explained, the sum of the total squares, and the sum of the residual squares, respectively. If there is an intercept term in the linear model, this coefficient of determination is actually equal to the square of the correlation coefficient between yi and yˆ.

$$R^2\left(\frac{\sum_{i=1}^{n} (yi - \bar{y})(\hat{y}i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(yi - \bar{y})^2\ \sum_{i=1}^{n} (\hat{y}i - \bar{y})2}}\right)$$

## 5. RESULT

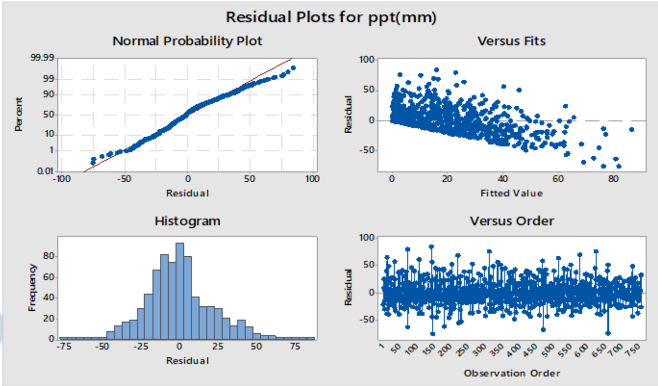



**FIGURE 1.1 TIME SERIES PLOT (ARIMA)**

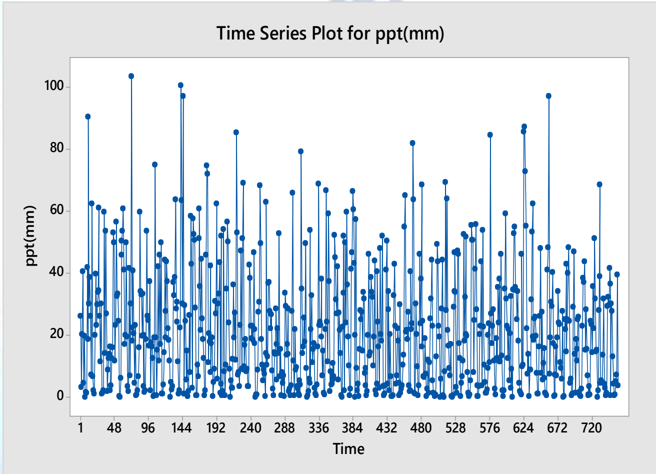



Figure 2. ACF of Residuals for ppt (mm)

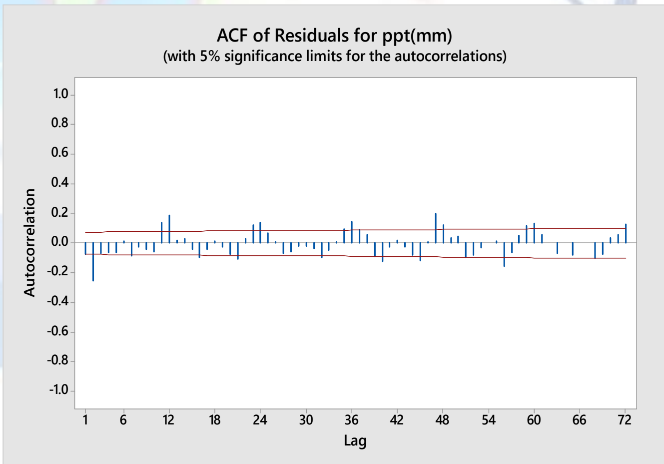
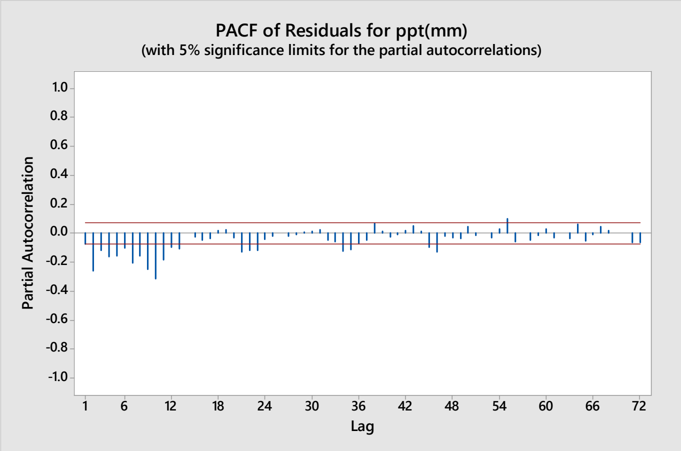



Figure 1.3 PACF of Residuals for Rainfall (ARIMA)




Given the P-value for the ARIMA model that equates to zero depicts that coefficients are statistically significant.

Table 1:

| Type | COEF | SE COEF | T | P |
|---|---|---|---|---|
| AR | 1 | -0.33871 | 0.0339 | -11.41 |
| CONSTANT | -0.070 | 1.039 | -0.07 | 0.946 |

Fast forward, the Mean square error also depicts that the model is best suited for the prediction.

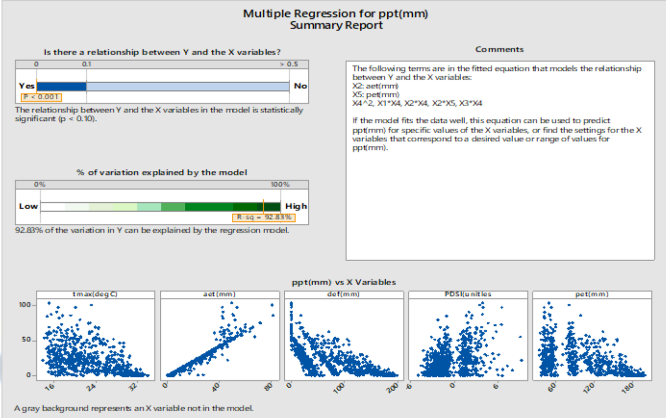
Table2: Modified Box-Pierce (Ljung-Box) Chi-Square statistic

| Lag | Chi | DF | P-Value |
|---|---|---|---|
| 12 | 284.2 | 10 | 00 |
| 24 | 329.6 | 22 | 00 |
| 36 | 349.1 | 34 | 00 |
| 48 | 376.0 | 46 | 00 |

Figure1.0-Figure 1.3 and Table 2 as displayed depicts that the ARIMA model is also ideal for the forecasting of precipitation judging from the $R^2$ value (90%). On top of that, the p-value also presents the ARIMA model as being fit for the task.

**Multiple Linear Regression**

The Multiple Linear Regression of precipitation from 1958-2020 of Alicante in Spain as depicted by the variables of signals a significant relationship between X and Y variables, given the R-square value which stands at 92.83%.



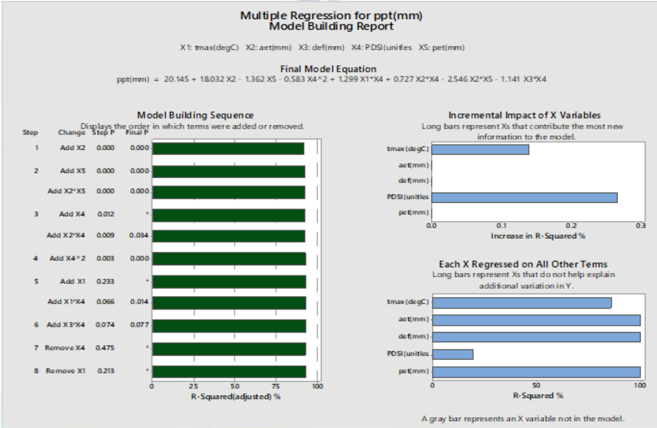




**Figure 1.5 MULTIPLE REGRESSION FOR (MLR)**

Figure 1.5 presents the results of a multiple linear regression analysis between a dependent variable (Y) and several independent variables (X). The purpose of this figure is to show the relationship between these variables and to assess the strength of this relationship. The P-value is a statistical measure of the significance of the relationship between the independent and dependent variables. A P-value less than 0.10 indicates that the relationship is highly significant, while a P-value greater than 0.10 suggests that the relationship is not significant. In this case, the blue color of the first calibrated bar in the upper left corner of Figure 1.5 represents a strong correlation, as the P-value is 0.001, which is less than 0.10. This suggests that there is a strong relationship between the independent and dependent variables in this model.

Additionally, the R-squared value of 92.83% in Figure 1.5 provides further evidence of the strength of this relationship. R-squared is a measure of the proportion of the variation in the dependent variable that is explained by the independent variables. A high R-squared value indicates that the model provides a good fit for the data and has a strong relationship between the independent and dependent variables. In this case, the high R-squared value of 92.83% suggests that the multiple linear regression model is highly effective in explaining the variation in the dependent variable, which is the precipitation.

In conclusion, the results depicted in Figure 1.5 indicate that there is a highly significant relationship between the dependent variable (precipitation) and the independent variables. The low P-value and high R-squared value provide strong evidence that the multiple linear regression model is well suited for predicting precipitation in Alicante, Spain.

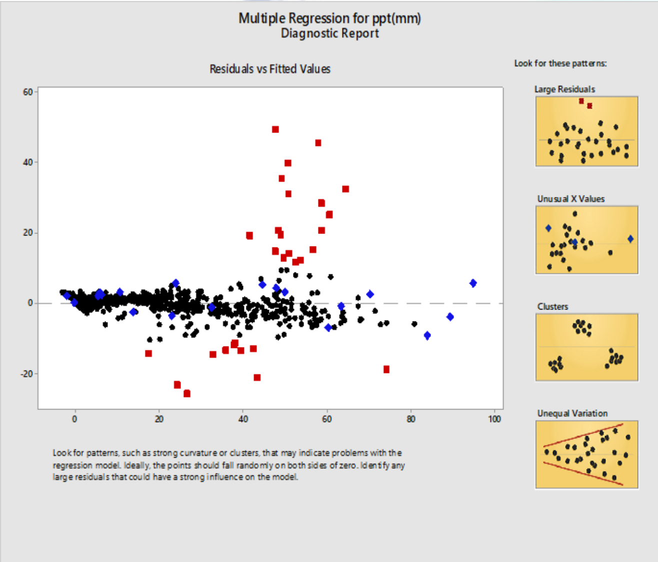



Figure1. 6 : Residuals Value Fitting plot

Figure 1.6 presents the results of a multiple regression analysis for the monthly precipitation (ppt in mm) in Alicante, Spain. The purpose of this figure is to provide a comparison between the residual and fitted values of the model. The residual value represents the difference between the actual and predicted values, while the fitted value is the predicted value of the model.

The R-squared value of 92.83% in Figure 1.6 indicates the strength of the relationship between the independent variables and the dependent variable (precipitation). In regression analysis, the R-squared value represents the proportion of the variation in the dependent variable that is explained by the independent variables. A higher R-squared value indicates that the model provides a better fit for the data and has a stronger relationship between the independent and dependent variables.

In this case, the high R-squared value of 92.83% suggests that the multiple regression model is highly effective in handling the prediction of precipitation in Alicante, Spain. The residual and fitted values in Figure 1.6 further support this conclusion, as they show that the model provides a good fit for the data and predicts the precipitation values with a high degree of accuracy.

In conclusion, the results depicted in Figure 1.6 indicate that the multiple regression model is a highly effective tool for predicting precipitation in Alicante, Spain. The high R-squared value and the comparison between the residual and fitted values provide strong evidence for the effectiveness of this model in handling the prediction of precipitation in the region.

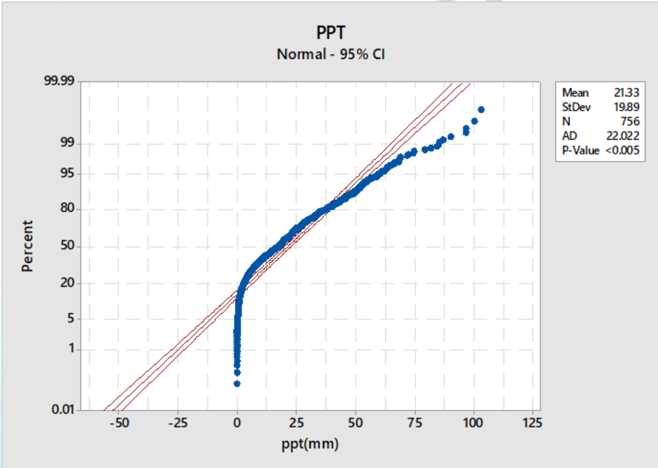



Figure 1. 7: PROBABILITY DISTRIBUTION PLOT FOR RAINFALL

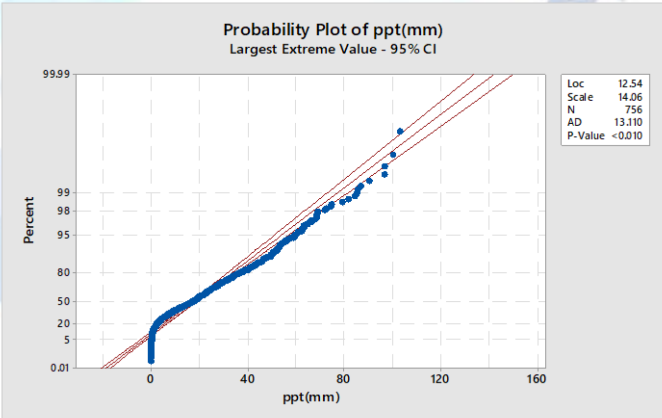



Figure 1.8 Probability of plot of ppt (mm)smallest Extreme Value

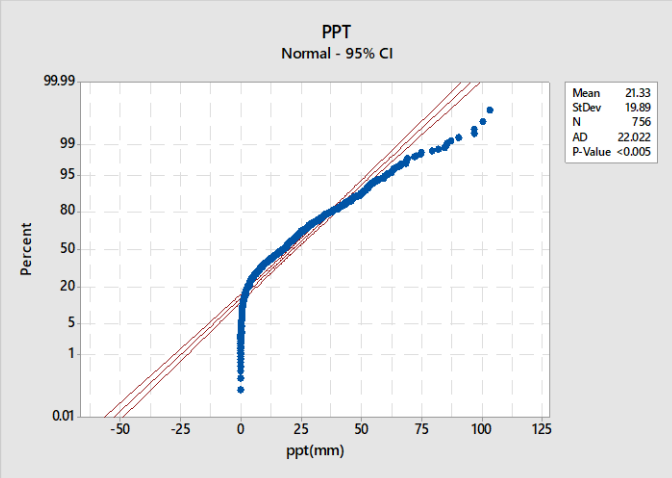



Figure 1.9 Probability plot of PPT ( mm) Largest Extreme Value

The probability plots in figures 1.7 to 1.9 are used to assess the normality of the data. The probability of fitness, as shown in these plots, is represented by the P-value, with a value of 0.05. A P-value of 0.05 or less indicates that the data is not normally distributed. On the other hand, if the P-value is greater than 0.05, it suggests that the data is normally distributed.

In this case, the results depicted in figures 1.7 to 1.9 indicate that the data is normally distributed, as the P-value is greater than 0.05. The value of the Anderson-Darling (AD) statistic, which measures the fit of the data to a normal distribution, is also shown to be 22.2. This value further supports the conclusion that the data is normally distributed.

In summary, the probability plots and the values of the P-value and AD statistic indicate that the data used in this study is normally distributed. This is important because many statistical models assume that the data is normally distributed, so this information can be used to inform the choice of the appropriate model for analyzing the data.

### Discussion

The results of the comparison between the ARIMA and MLR models for predicting annual precipitation in Alicante, Spain indicate that the MLR model is a better choice. This conclusion is based on several key factors. Firstly, the MLR model had five input parameters, which were used to analyze rainfall data from 1958 to 2020. This made it possible to estimate the amount of precipitation more accurately. On the other hand, the ARIMA model only utilized a single input parameter, which limited its ability to model the precipitation data accurately.

Moreover, the results of the auto-correlative ACF and Partial auto-correlative coefficient PACF for lags, which were used as the benchmark for estimating the ARIMA model parameters, indicated that the ARIMA model was suitable for data fitting. However, the R-squared value of 92.83% obtained using the MLR model indicated that it was much better suited for predicting precipitation in the study region.

In conclusion, the results of this research suggest that the MLR model is more effective for estimating monthly precipitation in Alicante, Spain. This model provides an accurate estimate of precipitation from available data, which makes it a useful tool for forecasting precipitation in the region. The use of multiple input parameters in the MLR model greatly improves its accuracy, making it a preferred choice for precipitation prediction compared to the ARIMA model.

## 5. CONCLUSION

In conclusion, the comparison between the ARIMA and MLR models for predicting annual precipitation in Alicante, Spain shows that the MLR model is a more suitable option. This is due to its ability to incorporate five input parameters, which provide a more accurate estimate of precipitation compared to the ARIMA model's single input parameter. The results of the study also showed that the MLR model had a higher R-squared value of 92.83%, indicating that it was a better fit for the precipitation data. Overall, the results suggest that the MLR model is an effective tool for estimating monthly precipitation in Alicante, Spain and should be preferred over the ARIMA model for this purpose.

### Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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